Journal of Open Innovation:
Technology, Market, and Complexity

Article

Trends, Impacts, and Prospects for Implementing Artificial Intelligence Technologies in the Energy Industry: The Implication of Open Innovation

Olesya Dudnik [1], Marina Vasiljeva [2,3,*], Nikolay Kuznetsov [4], Marina Podzorova [5], Irina Nikolaeva [6], Larisa Vatutina [7], Ekaterina Khomenko [8] and Marina Ivleva [9]

1 Department of Pediatric Dentistry and Orthodontics, I.M. Sechenov First Moscow State Medical University (Sechenov University), 119991 Moscow, Russia; Olesya.V.Dudnik@yandex.ru
2 Atlantic Science and Technology Academic Press, Boston, MA 01233, USA
3 Autonomous Non-Profit Organization "Publishing House Scientific Review" (Nauchnoe Obozrenie), 127051 Moscow, Russia
4 Institute of Digital Transformation Management, State University of Management, 109542 Moscow, Russia; nikolay.kuznetsov53@gmail.com
5 Department of Mathematical Simulation, Faculty of Fundamental Sciences, Bauman Moscow State Technical University, 105005 Moscow, Russia; marina.podzorova@inbox.ru
6 Department of Mathematical Economics and Applied Information Science, North-Eastern Federal University, 677009 Yakutsk, Russia; irina.v.nikolaeva@lenta.ru
7 Department of Public Administration and Law, Moscow Polytechnical University, 107023 Moscow, Russia; larissavatutina@yandex.ru
8 Department of Finance, Accounting and Mathematical Methods in Economics, Udmurt State University, 426034 Izhevsk, Russia; ekaterina.khomenko@yahoo.com
9 Humanitarian Training Center, History and Philosophy Department, Plekhanov Russian University of Economics, 117997 Moscow, Russia; marina.ivleva.2014@inbox.ru
* Correspondence: info@astap.net or marina.vasiljeva2017@gmail.com

check for updates

Citation: Dudnik, O.; Vasiljeva, M.; Kuznetsov, N.; Podzorova, M.; Nikolaeva, I.; Vatutina, L.; Khomenko, E.; Ivleva, M. Trends, Impacts, and Prospects for Implementing Artificial Intelligence Technologies in the Energy Industry: The Implication of Open Innovation. *J. Open Innov. Technol. Mark. Complex.* **2021**, *7*, 155. https://doi.org/10.3390/joitmc7020155

Received: 6 May 2021
Accepted: 10 June 2021
Published: 12 June 2021

Abstract: This research aims to substantiate the impact of using open innovation (OI) in the energy sector in readiness to implement artificial intelligence (AI) technologies and their effectiveness. The empirical method was proposed to determine the readiness level of OI for the implementation of AI technologies by comparing Russian and French energy companies. Readiness level indicators of companies for AI implementation using the Fibonacci sequence, Student's *t*-test, and the method of fuzzy sets were empirically determined. The integrated readiness indicator for AI implementation by companies was calculated using the method of fuzzy sets and expressed through variance, allowing for these significant factors. Russian companies are at a low level of developmental readiness to implement AI, which is in contrast to companies operating in a developed market where the determining factor is the AI technology cost. The example of the innovative business model "Energy-as-a-Service" shows the synergistic effects of OI use and AI technology introduction. This paper is novel because it seeks to contribute to the current debate in the literature, justifying the position that energy companies that have in the past actively applied the concept of open innovation in business, are the most competitive and most efficient in implementing AI technologies.

Keywords: open innovation; artificial intelligence; energy industry; efficiency improvement

1. Introduction

Efficient OI implementation by energy companies is conditioned by increasing interaction with customers, suppliers, and research institutions. Compared to the more one-sided internal models of innovation, the OI model offers significant benefits to the energy industry itself, the economy, and society. Despite the interest of energy sector companies to reduce production costs and improve process efficiency and innovative perspectives, few studies describe the mutual influence between implementing the OI paradigm and

AI. The tangible economic effect is the main goal of using OI and AI. The efficiency of AI implementation depends on companies' application of the OI concept, which increases their readiness to implement AI and creates a potential cumulative impact that has a synergistic effect on the competitiveness of companies in the global energy market.

Key trends contributing to the formation of a new technological paradigm in the world improve technological efficiency and reduce energy costs. AI is taking a higher priority [1]. It could be argued that the development of AI and machine learning software has gone hand in hand with the increasing viability and applicability of the energy industry. The benefits of specialized AI software from C3.ai enable the management of grid assets and provide the opportunity to predict and improve energy efficiency as a whole [2,3].

Active implementation of the OI and AI concept creates fundamentally new conditions for the functioning of the energy sector [4]. Energy companies have entered the era of active competition of open innovation technologies that can offer many energy supply options using various energy sources [5,6]. One of the key segments of inter-fuel competition will remain the electric power industry, which is especially relevant under the growing share of electricity in the final consumption of energy resources [7]. Significant progress in the cheapening of renewable energy technologies has made it possible to reduce production costs significantly. Still, many of them have already passed the main part of the learning curve, limiting the potential for further cost reductions. However, the time has come for renewables to learn how to compete in the market independently without reliance on large-scale government support. Competing fossil fuels are also making progress, contributing to intensified inter-fuel competition by optimizing costs along the entire chain and improving efficiency. At the same time, the mechanisms for power system operation will also change. This will be facilitated by the introduction of a set of innovative, automated, digital, and intelligent solutions, including technologies for predictive analytics, robotics, multi-level telemetry, smart grids, active-adaptive networks, microgrids, digital twins, Internet of Things, systems for collection, processing, and analysis of large amounts of complex data (Big Data), systems for storage and transmission of large amounts of encrypted data (blockchain platforms), and so on. All this opens, among other things, new opportunities for the functioning of energy storage systems and the development of distributed generation. The future configuration of energy systems and the role of fossil fuels in balancing uneven production and consumption will largely depend on progress in electricity storage. This problem has intensified for many countries by introducing RES capacities since the traditional unevenness on the consumption side has been supplemented by a significant unevenness on the production side [8].

AI has already changed the methods that many industries operate, and the energy sector is not an exception. Energy companies and individual consumers use AI to collect and analyze data to identify and track trends in energy sector production and consumption [9–13]. Therefore, in light of the increasing energy sector popularity, through the active use of AI technologies, companies have a great opportunity to use them to reduce costs, improve the safety, reliability, and sustainability of their systems, and reduce risks to gain competitive advantages [9,11,14]. The energy demand will only increase in the future.

Regardless of the industry and business activity, maintaining a competitive market position and business efficiency in current conditions depends on the AI implementation success and machine learning technologies that enable optimal business decisions [15–17]. AI creates surplus value for businesses because it helps to use the full potential of available data, makes reliable forecasts, and automates complex tasks. It also enhances productivity by automating business processes and targets that humans previously implemented [18]. A recent Frost and Sullivan analysis, "The Impact of Artificial Intelligence (AI) on Energy and Utilities", substantiated that AI will improve efficiency in the energy sector in the near term by automating operations in the energy industries [11]. This, in turn, will allow energy companies to use new business and service models. Global spending on AI is projected to double over the next 4 years, rising from USD 50.1 billion in 2020 to more than USD 110 billion in 2024 [19]. The AI practical use by energy companies worldwide is predicted to be USD 7.78 billion by 2024 and the average annual market growth rate from 2019 to 2024 to be 22.49% [20]. Experts predict that AI can provide faster decarbonization of the energy sector. It is expected that by 2050, energy sector sources will occupy a share of more than 80% of the energy mix, and their combination with the AI introduction and predictive algorithms can lead to even more efficient integration of these energy sources [21]. About 81% of the world's energy companies will implement AI in production by 2025, according to a study by EURELECTRIC, the European electricity association [21].

Russia, characterized by its advanced positions in nuclear weapons and space technology development, does not occupy a significant place in AI development and implementation. It ranks 30th out of 54 countries studied [22]. Nevertheless, it should be pointed out that the national government is promoting initiatives in these developments [23]. It is proved by the establishment of the AI Center at Moscow Institute of Physics and Technology and financial planning for the industry for 5 years of USD 2 billion according to the National Strategy for Artificial Intelligence Development until 2030 [24]. The size of state investment in Russia is not inferior to that in the USA and UK [22]. The popularity of AI by businesses in Russia is also increasing. According to Worldwide Artificial Intelligence Spending Guide 2019 assessments, Russian spending on AI was determined to be USD 172 million (at the end of 2019) with 30% annual growth [25], but it remains relatively insignificant. By comparison, investment in AI in Europe exceeded USD 7 billion in 2019 and the USA exceeded USD 16.5 billion [26].

There are many expectations associated with the Russian market of AI systems, from the rapid growth of innovative domestic technologies to a powerful wave of practical implementations based on the most advanced innovative developments. The financial industry remains the leader in the number of business projects for AI implementation [25]. Here technology allows for cost reduction, risk minimization, verification of borrowers, and their capacity to pay, forecasting, and so on [27]. Manufacturing, wholesale and retail trade, and the public sector are beginning to implement AI well behind Russia's financial and energy sectors [28]. Today, only 11% of energy companies are beginning to implement AI technologies [29]. Nevertheless, about 43% of Russian businesses do not use AI technology in their business activities and do not plan to use it entirely. Business leaders understand the effect of such innovations only in increasing productivity by reducing costs and more accurate forecasting of consumer demand, which can be achieved by cheaper alternative means of innovation [25]. The strategic goal of Russia is to ensure its energy independence and competitiveness in the short term. However, the lack of development of AI technologies and the unpreparedness of the energy sector to implement them actively in practice may provoke the risk of Russia's economic and technological gap by 2024. Therefore, this study aims to identify the key factors having a destructive and deterrent effect on readiness for AI technologies of companies generating energy sector and determine the current readiness level of such companies operating in an emerging market environment for the case of Russia. It also aims at identifying the distinguishing factors of readiness for AI of companies operating in the energy sector industry in a developed and developing economy.

According to the new "Energy Strategy of Russia for the period up to 2030" [30], energy companies should be oriented towards using their potential as effectively as possible by increasing the innovation component in their activities and introducing "Energy-as-a-Service" (EaaS) approach [31]. EaaS is a packet service model which provides the customer with hardware, software, and energy services. EaaS solutions should include consumption management and energy efficiency services, facilitate the introduction of RES and other decentralized energy sources, and optimize the balance between supply and demand in the electricity market. The main advantage for the consumer is the simplification of the service package despite their growing diversity [32]. The transition to the EaaS model can be accomplished in several stages. First, it is necessary to integrate AI technologies into core processes for expanding the range of products and services and, finally, to develop comprehensive energy packages according to the EaaS concept [31].

AI is most commonly understood as an engineering technology dealing with cognitive tasks typically destined for human intelligence, such as learning, problem-solving and pattern recognition, data aggregation, processing, and so on [33]. An efficient AI system can "think" faster and process more information than any human brain [34,35]. AI is based on various machine-learning technologies that recognize patterns in data and generate projections. AI creates surplus value for businesses because it helps to use the full potential of available data, makes reliable forecasts, and automates complex tasks. It also enhances productivity by automating business processes and targets that humans previously implemented [18,36–38].

Many Russian energy companies are now improving growth rates and productivity with AI solutions [8,39,40]. The result of the first wave of AI implementation has been the penetration of "intelligence" into business processes and efficiency improvements [41]. However, the second wave of AI implementation brings deeper transformations and creates opportunities for the most remarkable innovative breakthroughs. This is about creating new economic opportunities for the energy industry [4,42] and solving many pressing human problems, from ecology to radical changes in health and well-being [10,41,42]. The greatest effect here could come from the cooperation of Russian energy companies with innovative start-ups, research centers, and universities that can extract new value from various AI technologies. Therefore, at the present stage, an indispensable condition for the development of the energy industry is its readiness to implement AI through OI. The concept of OI aims to ensure the openness of the innovation process for experts from other areas. At the same time, the traditional model implies reliance on the internal human capital of the company [3,43–45]. OI accelerates the movement of internal and external information flows, opens new perspectives at all stages of the value chain [46,47].

The technological paradigm in the global EI has now reached its efficiency limits. The development and implementation of OI will be an absolute necessity in areas where accessibility, reliability, and quality of energy supply are in high demand [5,6,48]. OI in the energy sector optimizes the use of existing infrastructure and incorporates the latest energy storage systems, regulated consumption solutions, and systems used to organize energy services close to consumers and based on 110 kV distribution grid infrastructure and below into the generation and distribution process [49].

The strategic goal of Russia is to ensure its energy independence and competitiveness in the short term. However, the lack of development of AI technologies and OI and the unpreparedness of the energy sector to implement it actively in practice may provoke the risk of Russia's economic and technological gap by 2024. Therefore, this study aims to identify the key factors having a destructive and deterrent effect on readiness to develop OI for implementation of AI technologies of companies generating energy and determine the current readiness level of such companies operating in an emerging market environment for the case of Russia. It also aims at identifying the distinguishing factors of readiness for AI of companies operating in the energy sector industry in a developed and developing economy.

2. Literature Review

2.1. Open Innovations for AI Implementation in the Energy Sector

The OI process initiated by multinational energy companies overcomes not only geographical but also institutional and disciplinary barriers. By bringing together a wide range of actors in innovation systems (enterprises, the public research sector, and customers), this process forces them to adapt their business models to increasing global competition, which is increasingly based on OI and knowledge [1]. This trend poses no less of a challenge also to state energy policy. Its traditional approaches and tools may not be efficient enough to allow the country to take maximum advantage of the globalization of innovative markets and networks. The only effective strategy in such circumstances can be offensive, involving the development of international relations in all forms, emphasizing small and medium-sized businesses, which will lead to the strengthening of national and regional innovation systems. In addition, the state is intended to ensure the most favorable framework conditions for innovation, including specialized research and development infrastructure, to attract and retain highly mobile investments in knowledge and talented people [50].

OI in the global energy sector is a set of processes that lead to new or improved technologies that increase the diversity of energy resources used, increase the reliability of energy systems, and reduce the economic, environmental, and political costs associated with electricity generation and distribution [51,52]. OI in energy is a process reflected in the market share and other factors related to the dissemination of new energy technologies. The process begins with the invention of the technology and ends with its dissemination [52]. Dissemination of innovations in the energy sector refers to demonstration projects that play a vital role in the commercialization of innovations in the energy sector [49,53]. The level of technical novelty in the electricity sector plays a key role in their dissemination [54].

Innovations in the global EI are closely linked to changes in technology, but it is not worth saying that this is the only type of innovation possible in this industry. The EI companies are changing when introducing organizational innovations caused by changes in the market environment [55,56].

Studying the theoretical basis of innovation in the global energy sector requires further classification since technological innovation in the energy sector is twofold. On the one hand, energy is a factor of production that has some value. On the other hand, energy transformation is part of the innovation process, creating disruptive innovation [49,57].

AI is not one technology but a collection of multiple technologies, the full effect of which can be felt only when they are used together [23]. Since not all energy companies are ready to spend significant resources on the internal development of AI technologies, cooperation with other organizations may be a solution. Companies should understand what an area of transformational change is and what a growth point is. Additionally, the energy sector must radically change its strategies for training, performance assessment, and engaging AI implementers. They will need to train staff in new skills and retrain them at a rate and scale higher than the market as a whole, and they will need to keep staff at the appropriate skill level at all times. The optimal use of AI technology will have to empower professionals, helping them be more efficient and do their jobs more creatively, accurately, and qualitatively. This includes building a culture of continuous learning, which is possible largely due to new technologies such as personalized online courses replacing traditional educational programs and gadgets like "smart glasses" that help improve employees' knowledge and skills in parallel with their daily duties [18]. Partnerships with start-ups, universities, and individual experts that open up access to global knowledge and skills ensure that energy companies are efficient in this area.

The true value of AI for the energy sector is not in some algorithm or neural network per se but rather in how data analytics can change the way of doing business. For using AI technology effectively, it is necessary to have access to a large variety of data, not just a specific part of the dataset. Therefore, OI allows energy companies to share data in a secure environment, secures information, and ensures that members can share it fearlessly on an ongoing basis to develop the energy market as a whole.

OI opens up access to AI and encourages energy companies to use new technologies that may otherwise be out of their reach due to their high cost or long development cycles [51]. Companies can use a range of AI frameworks and technology platforms, such as Gigster. This platform brings together leading AI developers and designers, or cloud services of Microsoft Azure Machine Learning and Amazon Machine Learning [58].

2.2. *Artificial Intelligence in the Energy Sector*

Scientists began to study AI as a new prospect in the middle of the 20th century. Its prerequisites were the emergence of the foundations of the *mathematical theory of computation* (algorithmic information theory) [59] when the first computers appeared and the Turing Test was developed. However, the term "artificial intelligence" first came into scientific use only in 1956, at a conference at Dartmouth University in the USA during a six-week discussion among scientists such as McCarthy, Minsky, Shannon, and Turing [60]. Then, one could observe significant steps forward in AI development due to large-scale funding of initiatives by military research organizations. In the USSR, work in AI began in the 1960s. In 1964, the Leningrad logician Sergey Maslov published the work "Inverse method for deducibility detection in classical predicate calculus" [61]. In this work, the method of automatic search for theorem proving in predicate calculus was proposed for the first time. In 1966, V. F. Turchin developed the language of recursive functions "Refal" [62]. Until 2016, AI research and development have responded by developing AI as a system capable of self-learning without outside assistance [63]. However, since 2016, there are many subject area involvements in AI with more practical relevance to AI than a fundamental one. One of the main directions in AI has become the study of ways to create AI, representing the integration of already developed AI systems into a single system capable of solving humanity's problems [34].

AI research initially focused on enough broad range of issues and applications within the concept of Industry 4.0 (the fourth industrial revolution), adding to the controversy over the stage of technological and economic development in current conditions and how innovative technologies will and can ensure the sustainability of economic growth [64–66]. The fourth stage of the industrial revolution is characterized by the introduction of cyber-physical systems into factory processes. These systems are expected to network together, communicate with each other in real time, self-adjust, and learn new behaviors. AI solutions are now an integral part of the implementation of Industry 4.0 projects [7,64,67]. For example, there are (1) "narrow" AI, which automates decision-making in a specific area, (2) "broad" AI, which works in various tasks and areas that are more diverse without significant changes in methodology, and (3) "general" AI, which is closest to the capabilities of the human brain [68]. General AI is rather the ultimate aim of concept development. Now it is an elusive ideal limited by the current technological level of civilization.

As communication systems and tasks become more and more complicated, researchers have focused on a whole new level of "intelligence" of supporting software systems, such as protection against unauthorized access [69], the security of information assets [70], protection against attacks, semantic analysis and online searching [69,70], and so on. On the other hand, as the globalization of economic life raises competition to a fundamentally different level, many studies have emerged in the area of business and resource management system efficiency [71–73], analytical capabilities, and trend forecasting in the economy [15], as well as radical improvements in labor efficiency, reducing the financial and labor costs of doing business [18,74], increasing sustainable economic growth through green economy development [75], and so on. Recently, scientists have been particularly interested in studying AI in terms of the ability to make the right business decisions and reduce business costs [76]. As the commercial potential of AI technologies moved beyond clearly laboratory research, they become of economic value. Therefore, in current conditions, a cycle of engineering technology development has come when even small improvements in function lead to a marked increase in economic value, thereby increasingly attracting investors.

Most scientists hold the viewpoint of the positive impact of the practical AI technology implementation on energy sector development and the economy as a whole [18,33,69,75] and human capital potential [77]. Within this spectrum, a dominant number of papers focus specifically on demonstrative assessments of the possible impact/effects of digitalization on particular industries and groups of industries in the global economy [12,13,18,33,72,77] and empirical assessments of digitalization effects of using machine intelligence [78–80]. Although, some scientists investigate the threats to energy security that AI technologies may carry. According to research by Oxford professor Nick Bostrom, by 2022, AI will begin to think about 10% like a human, by 2040, 50% like a human, and by 2075, the thinking processes of a robot will be indistinguishable from human thinking [81]. The topic of humanity's future, confrontation with machines, and, conversely, hybridization drew to light new various concerns and terms. These include transhumanism and technological singularity. It is the point in time when computers, in all their incarnations, will become smarter than humans are. When this happens, computers will grow exponentially compared to themselves and reproduce themselves, and their intelligence will be billions of times faster than human intelligence. It is predicted that this moment could come in 2030. The principal representative of this idea is Raymond Kurzweil [82].

However, most modern scientists assess the AI contribution to the development of the energy sector as positive. They deepen their research by evaluating the complementary and destructive factors of developing and implementing these technologies in business. In doing so, they highlight abilities, investment, and leadership attitudes [83,84] as the underlying drivers of energy economy readiness for AI, which put developed countries and China at the top of all ranking scores on the level of AI implementation in the energy sector [85].

Appendix A (Table A1) shows the results of research into the use of AI methods in the energy sector [2,86–105]. It should be noted that the most promising groups of tasks where AI using OI can affect are the next:

- Forecasting (meteorological information, equipment operating conditions, consumption changes, and so on);
- Optimization (modes of operation of power system components, consumption, network configuration, and so on);
- Management (artificial lighting, RES and batteries, asset performance, and so on);
- Communication (energy companies with consumers);
- Development of services (in terms of customer satisfaction with the range of services provided by companies, participation of companies in energy markets, addressing quality assurance issues).

Thus, further expansion of the use of AI tools in the energy sector will inevitably take place alongside unfolding processes such as:

- Energy transformation, driven by the increasing use of local RES as well as the intelligent production, transmission, and consumption of energy (smart technologies);
- Digital transformation, driven by the increasing need for monitoring and analysis of data (Big Data) as well as the introduction of new technologies (e.g., blockchain, digital substation, unmanned devices for surveillance of facilities, and so on);
- Integration and mutual influence of different sectors of the energy and transport sectors (e.g., power-to-X technologies).

Given the above, there is no doubt that the energy sector positions as one of the most interesting applications of AI methods will strengthen.

Despite growing interest, academic contributions to energy-related AI and OI research in emerging economies remain insignificant [85]. The institutional environment in developing countries is very different from that in developed countries. Such a situation creates barriers and challenges to AI-based energy sector applications [10,106]. In Russia, scientists consider the benefits of using AI as a rule to militarize the economy [107,108]. This specificity of scientific research comes from the fact that public funding leaders are AI projects for the public sector, transport industry, defense, and security [109]. It indicates that Russia primarily supports projects with rapid anticipated practical application. For example, data analysis and various recognition systems help to optimize logistics and transportation problems. Current geopolitical challenges also determine the urgent need for intelligent systems for the modernization of the military-industrial complex. However, since Western scientists are actively studying new AI and OI conceptual frameworks in the energy sector, and their energy efficiency has been clearly proven, there is a need to search for AI development readiness factors to find and identify the most significant areas for the efficient use of AI in companies generating energy sector with a focus on emerging markets. Empirical research can help companies identify and understand the AI disruptive potential and the obstacles and challenges associated with AI implementation and integration in the energy sector in emerging economies.

The following hypotheses were developed proceeding from the established research aims:

Hypothesis 1 (H1). *The energy industry is on its way to a new business concept, named Energy-as-a-Service (EaaS), which implies providing new energy services directly to the consumer. EaaS includes consumption management, consumption optimization upon the availability of a local source and battery, energy exchange through the local grid, or energy savings. The implementation of this business concept necessitates the introduction of OI and AI in the energy industry around the world. Increasing readiness to implement OI and AI technologies is intended to make the energy industry cheaper to produce and more competitive.*

Hypothesis 2 (H2). *The tangible economic effect is the main goal of using AI. From this point of view, the companies that have long and actively applied the concept of OI in business are the highest priority for AI implementation because they are the most competitive and the most efficient in introducing new technologies. It is precisely such companies that should ensure significant economic growth in the industry. Priority energy companies for AI implementation should first be selected based on their readiness to implement AI and the potential cumulative effect that the impact will have on the country's overall economic growth. The main prerequisites for the successful implementation of AI and OI in the Russian energy sector are public funding and efficient business cooperation based on specialized strategies (road maps) that consider the level of innovation management, the quality of human capital, and scientific activity.*

Hypothesis 3 (H3). *It is appropriate to apply the proposed empirical method for determining the readiness level to AI technologies of companies operating in the energy industry. The integrated readiness indicator for OI and AI implementation of companies can be calculated using fuzzy sets and expressed through variance, taking into account the importance of the factors.*

3. Methodology

3.1. Conditions of the Survey Aimed at Assessing Readiness of Companies to Develop OI for AI Implementation

This study is based on the evaluation technique of technological readiness and its variations [110,111]. These methodologies involve a questionnaire-based assessment of readiness to develop OI for AI implementation by evaluating motivating factors (which positively affect the ability to implement AI) and inhibiting factors (which inhibit AI implementation). Motivating factors, according to [110], are optimism (the belief that technology and innovation have positive benefits) and innovativeness (an inborn tendency to experiment). Inhibiting factors are discomfort (lack of control over technology) and insecurity (technology can adversely affect the user and society). According to these directions, given the list of questions used in [110,111], the current economic situation, and the AI application experience in Russia, survey questions were compiled to assess the readiness of companies operating in the energy sector industry to develop OI for AI implementation. The survey questions and notation of the indicators used in the study are given by reference [112]. The survey was conducted once a quarter for 2018–2020. Twelve surveys in total were conducted as part of this study. The respondents were 684 people—representatives (employees and managers) of 45 companies operating in the energy sector industry in Russia. The number of completed questionnaires received each time was between 547 and 684. For comparing the level and dynamics of readiness of companies operating in the energy sector industry to develop OI for AI implementation in Russia and Western Europe, a similar survey was conducted among representatives of French companies during February–June 2018 and February–June 2020. As an object of comparison, France is selected according to the results of clustering countries of the world by the AI Readiness Index [14] and indicators of the use of AI [8]. For the study, companies managed on an OI basis were selected, which invested significantly in the OI implementation in 2014–2018. The analysis of such companies in Russia is given in [113].

The indicators proposed by Stanford University for clustering are, per capita, the number of AI conference reports, number of report citations, number of AI papers, number of AI paper citations, number of AI patents, number of patent citations, amount of investment in AI, and number of funded AI development start-ups. Thus, the studied indicators made it possible to cluster countries according to the current level of AI development (the number of publications and patents and their citations, amount of financing) and its potential (the level of human capital development, infrastructure, and the state of legal regulation). The use of per capita indicators of AI development in clustering made it possible to ensure comparability of research results regardless of the country's size.

Clustering was conducted based on 2020 data for 26 countries leading in AI use for which data are published. Three country clusters were determined according to the level of AI development, using hierarchical clustering and k-means. The adequacy of the clustering results is evidenced by the intergroup variance values (Between SS), which exceeds the intragroup variance (Within SS); F-criterion, the calculated values of which exceed the tabulated 3.42 at a significance level of 0.05, and signif. $p < 0.05$ for all indicators (Table 1).

Table 1. Clustering indicators of countries by level of AI development.

Variable	Between SS	Within SS	F	Signif. p
Number of reports at AI conferences per capita	5823.51	4699.56	14.25	0.0001
Number of citations of AI reports per capita	10,206.35	3936.83	29.81	0.0000
Number of AI papers per capita	4853.57	2459.47	7.48	0.0031
Number of citations of AI papers per capita	5648.68	4242.57	15.31	0.0001
Number of AI patents per capita	17,816.65	5099.55	40.18	0.0000
Number of patent citations per capita	15,454.24	4477.93	39.69	0.0000
Amount of investment in AI per capita	7427.63	6772.68	12.61	0.0002
Number of funded AI development start-ups per capita	430.45	173.42	30.04	0.0000
AI Readiness Index	297.27	107,52	3.79	0.0321

According to the clustering results, Singapore and Switzerland formed the cluster of countries with the highest level of AI development (Cluster 1). In terms of AI development, Finland, France, Japan, the United States, and South Korea follow them (Cluster 2). Russia is in Cluster 3, characterized by the lowest level of AI development per capita of the countries under review. Based on this, for Russia at this stage, the target parameter of AI development is to move to Cluster 2. Based on the Euclidean distance between countries that formed cluster 2 and the center of this cluster, France, with the minimum distance, is the representative cluster country. Therefore, this study compares the development levels of readiness factors to implement AI in Russia and France (as a benchmark of AI development for Russia at this stage).

France is also actively developing the energy sector, as evidenced by one of the world's leading positions in the global wind energy market [29], with a high-efficiency level in this type of energy. This industry companies in France have experience in AI implementation, which has a positive impact on the industry's efficiency. Thus, the use of French companies in this study made it possible to explore the best AI practices for energy sector development based on a comparative assessment of the factors that determine the readiness of companies to implement AI and the level of their development.

The survey involved 396 people—representatives of 24 companies in France. All of them sent inquiry returns based on the results of the first survey stage. According to the results of the second survey, 388 questionnaires were answered. The survey was conducted using Google Forms. Business representatives, who understand the essence of AI, previously had an experience of its use, or were aware of its opportunities when using in companies operating in the energy sector industry, took part in the survey.

Forty-five enterprises in Russia and 396 representatives of 24 enterprises in France took part in the survey. The respondents were men (65.9%) and women (34.1%) under the age of 25 (15.6%), 25–44 (70.8%), 44–60 (13.6%). By status in the company, 15.9% were employees, 44% were low-level managers, 31.7% were middle managers, 6% were senior managers, and 2.3% were business owners.

In scale, most enterprises have branches and subdivisions on the territory of more than three regions of Russia/France (49.3%), on the territory of 2–3 regions (24.6%), in other countries (5.8%). In total, 20.3% operate in one region.

The representativeness of the survey results is evidenced by the number of sampling population (547–684 people in Russia and 388–396 people in France) with the sufficient number of 384 people determined based on the 95% confidence probability, ±5% confidence interval, and the size of general population > 30 people. The representativeness is also evidenced by the fact that the survey participants had different ages, statuses in the company (employees, managers of the lower, middle, upper level, and owners), work experience, and education. Participation in the survey was voluntary, and the results were anonymous to other respondents.

Questions 1–8 of the questionnaire were used to obtain the characteristics of the business and the respondents themselves, which may affect the study results. The readiness degrees of companies to develop OI for AI implementation and the factors that determine them are evidenced by the results of the answers to questions nos. 9–45. Responses to Questions 9–11 were quantified on the next scale: answer *a* corresponds to a score of 0 points, answer *b*—5 points, answer *c*—10 points, and answer *d*—15 points. Quantitative assessment for questions nos. 12–45 is represented by integers in the range of 0–5 points, according to the assessment scheme specified in the respective question.

The reliability of the proposed questionnaire is evidenced by the value of Cronbach's alpha (Table 2), calculated using Statistica 12.0 software, and the total percentage of variance according to the factor analysis results by principal component analysis (PCA).

Table 2. The questions' reliability factors in determining the readiness of Russian and French companies operating in the energy sector industry to develop OI for AI implementation.

Question No.	Alpha If Deleted [1]	Question No.	Alpha If Deleted	Question No.	Alpha If Deleted	Question No.	Alpha If Deleted
9	0.91	19	0.9	28	0.87	37	0.89
10	0.9	20	0.88	29	0.9	38	0.9
11	0.88	21	0.86	30	0.91	39	0.88
12	0.9	22	0.89	31	0.90	40	0.89
13	0.81	23	0.91	32	0.89	41	0.87
14	0.86	24	0.87	33	0.91	42	0.89
15	0.89	25	0.86	34	0.88	43	0.88
16	0.9	26	0.9	35	0.89	44	0.89
17	0.88	27	0.91	36	0.87	45	0.87
18	0.87						

[1] The reliability of the questionnaire was checked for each survey. The table shows the average values of Cronbach's alpha for the questions for the survey period (2018–2020) in Russia and France.

The average calculated value of Cronbach's alpha was 0.89. It indicates the questionnaire's internal consistency and ability to describe the factors determining business readiness to develop OI for AI implementation. For questions nos. 9–10, 12, 16, 19, 23, 26–27, 29–31, 33, 38, the Cronbach's alpha values are above average. It means that excluding these factors from the questionnaire will lead to greater consistency. On the other hand, their exclusion leads to a significant decrease in the cumulative percentage of variance from 89.4–92.0% to 84.6–85.4%. To preserve informativeness and considering that the proposed questionnaire is reliable based on the overall Cronbach's alpha (0.89), the questions were not excluded from the questionnaire.

To process the results obtained and confirm the questionnaire informativeness (through the cumulative variance index), PCA was conducted according to the results of each survey. The points for the questions involving quantitative evaluation (nos. 9–45) corresponded to variables. The variable AI_9 corresponded to question no. 9, the variable AI_{10}—to question no. 10, and so on. The number of observations corresponded to the number of questionnaires: $N \in (547; 684)$ for Russia and 388, 396 for France between 2018 and November 2020. Exceeding the number of observations over the number of variables by more than $2n + 1$

times (where n is the number of variables, n = 37) indicates the sample sufficiency for PCA [114].

3.2. Assessment Model of Business Readiness to Develop OI for AI Implementation

The readiness indicator to develop OI for AI implementation is proposed to calculate using fuzzy sets. The advantage of this method is that it allows you to obtain an integrated quantitative and qualitative assessment (readiness level) based on the levels of individual indicators. The use of individual indicator levels provides a balance of indicators when a super-high value of one indicator cannot compensate for the low values of others, which is possible when calculating the integrated indicator based on additive or multiplicative convolution. The levels of indicators are determined based on the absolute values of the indicators for Questions 9–45, taking into account potentially minimum and maximum values. Potentially minimal value is 0 points, maximal for question no. 9–10 points, no. 10–5 points, no. 11–15 points, nos. 12–45–5 points. The levels obtained this way reflect the current situation of the phenomenon under analysis and allow for the classification of the entire possible range of values.

The probability of attributing the points for questions nos. 9–45 to levels (low, medium, high) is determined based on the trapezoidal membership function. According to the function chosen, there is a range of indicator values, which corresponds to 100% confidence in attributing the indicator value to a defined level. There are also a range of 0% confidence and intermediate values, for which the probability of attributing to the level is in the interval of (0%; 100%). For each indicator, the range of actual and potential values for the entire study period (2018–2020) was divided into three levels according to the Fibonacci sequence. It was adjusted by narrowing the range of values of these levels until the differences in the values of the indicators between the levels became statistically significant, according to the t-test. The data set for determining the levels consisted of 8125 observations (the total number of questionnaires for Russia and France during the study period). For determining the probability of attributing to the level of intermediate values of indicators that have not formed ranges of 100% confidence, it was proposed to use the formula:

$$\begin{aligned} \mu_{(L)} &= \frac{AI_i'' - AI_i}{AI_i'' - AI_i'} \\ \mu_{(H)} &= 1 - \mu_{(L)} \end{aligned} \tag{1}$$

where $\mu_{(L)}$ is the probability of attributing the i-th indicator to the lowest of the two possible levels. Possible levels are those for which $\mu \neq 0$; $\mu_{(H)}$ is the probability of attributing the i-th indicator to the highest of the two possible levels; AI_i is the score for the i-th question (the value of the i-th indicator), $AI_i \epsilon (AI_i'; AI_i'')$; $(AI_i'; AI_i'')$ is an uncertainty zone between the lowest ($\leq AI_i'$) of the two possible levels and the highest ($\geq AI_i''$), between which there are statistically significant differences by t-test.

The readiness-integrated indicator of companies to develop OI for AI implementation is determined by the formula:

$$I = \sum_{i=1}^{n} k_i \times (w_1 \times \mu_{i1} + w_2 \times \mu_{i2} + w_3 \times \mu_{i3}) \tag{2}$$

$$k_i = \frac{d_j}{\sum_{j=1}^{N} d_j} / l_j \tag{3}$$

where k_i is the rating of the i-th indicator; μ_i is the probability of attributing the i-th indicator to the levels (μ_1—low, μ_2—medium, μ_3—high), calculated based on 100% confidence zones and intermediate probabilities calculated by the formula (1); $w_1 - w_3$ are adjusting factors corresponding to the values w_1 = 0.1, w_2 = 0.5, w_3 = 0.9 [115].

Questions nos. 13, 15–16, 22–25, 27, 30–31, 39, 42–45 characterize the possible threats when using AI. The higher the level of indicators AI_{13}, AI_{15}, AI_{16}, AI_{22}, AI_{23}, AI_{24}, AI_{25}, AI_{27}, AI_{30}, AI_{31}, AI_{39}, AI_{42}, AI_{43}, AI_{44}, AI_{45}, the lower the readiness to implement AI. Therefore, for these indicators when calculating the integrated indicator w_1 = 0.9, w_2 = 0.5, w_3 = 0.1; D_j is the variance of the j-th factor, which includes the i-th indicator; l_j is the number of indicators included in the j-th factor; n is the total number of indicators (n = 37); N is the number of significant factors (N = 6).

Ratings of the indicators are calculated by dividing the variance of the factor by the number of indicators that form this factor. With this calculation method, the sum of the ratings of all indicators in the integrated model is 1. It makes it possible to ensure the commensurability of the integrated indicator by year as the indicator maximum value I_{AI} does not depend on the factor composition. Respectively, the calculated levels of the integrated indicator are universal, and there is no need to recalculate them according to the results of each questionnaire. The levels of the integrated indicator (low, medium, high) are determined similarly to the levels of individual indicators AI_i.

4. Results

4.1. Energy-As-A-Service

Energy-as-a-service (EaaS) is an innovative business model that involves the cumulative use of an open innovation approach and AI technology implementation. Figure 1 visually presents the synergistic effect of AI and AI tools on developing the EaaS concept. EaaS is a packet service model which provides the customer with hardware, software, and energy services. EaaS solutions should include consumption management and energy efficiency services, facilitate the introduction of RES and other decentralized energy sources, and optimize the balance between supply and demand in the electricity market. The main advantage for the consumer is the simplification of the service package despite their growing diversity [17]. This scenario requires a material, digital, and communication infrastructure, which means that different categories of players can operate in the EaaS market: utilities and industrial enterprises, technology companies, large oil and gas companies, specialized renewable energy providers, telecommunications companies, and young innovative companies (start-ups). Depending on who will ensure the balance of power in the new market and how widely innovative technologies will be introduced, four development scenarios are possible: “EaaS-service providers”, “infrastructure solution providers”, “dying giants”, or “stagnating utilities”. To adjust to the new realities, organizations will have to change their business models, and in some cases, the changes will be significant. The same trends that in due time had a significant impact on retail, transportation, and consumer electronics are now coming to the energy markets. Companies need to understand what opportunities they can use, what competencies they need to develop, and what market segments are the most promising for further growth. The transition to the EaaS model can be accomplished in several stages. First, it is necessary to integrate AI technologies into core processes; second, expand the range of products and services; and finally, develop comprehensive energy packages according to the EaaS concept [31].

The model presented in Figure 1 is based on the assertion that effective implementation of the EaaS model is only possible in companies using open innovation, implemented AI technologies, and applying tools of energy efficiency improvement. The OI concept module will help energy enterprises identify, acquire, transform, and apply innovation resources, facilitate generating knowledge resources, and user interaction behavior will help enterprises effectively choose high-quality knowledge resources through collective knowledge. With high-quality knowledge management capabilities, enterprises can transform external users’ knowledge resources to improve their innovation performance. Improved innovation performance attracts more users, which has a positive impact on innovative and user interaction behavior. An effective management mechanism improves knowledge management capabilities, which has a positive impact on innovation performance, helping companies generate more innovation revenue and accelerate their development.

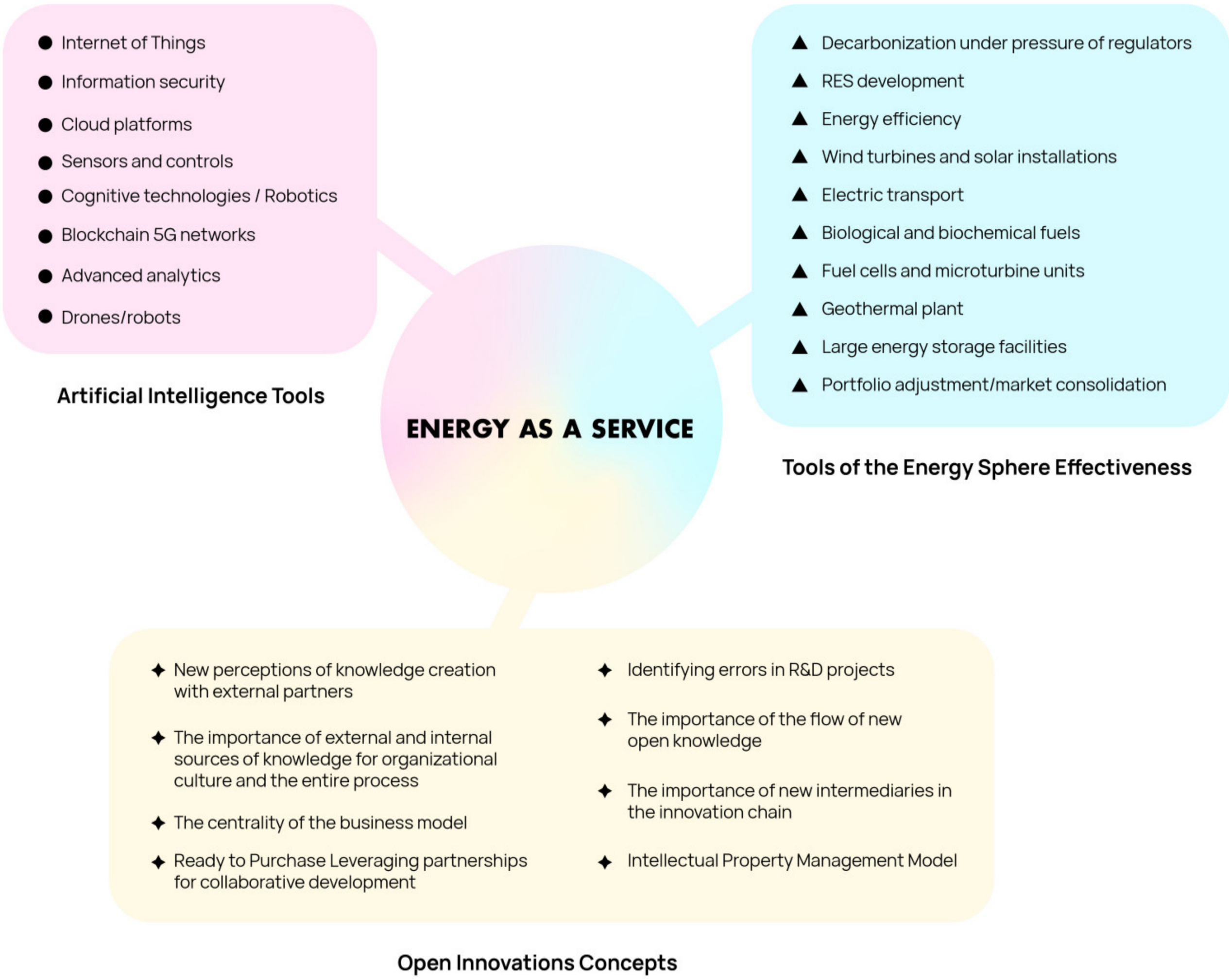

Figure 1. Conceptual model of the cumulative effect of OI and AI on EaaS.

The introduction of the EaaS concept shifts the emphasis from centralized, asset-oriented power generation and sales to passive customers. Instead, it offers end-to-end management of energy assets and customer services. This requires the cumulative use of all technologies presented in both AI Tools and Tools of Energy Sphere Effectiveness blocks. Thus, the companies planning to implement EaaS need to assess their readiness to implement AI technologies.

4.2. Readiness Factors of Companies to Develop OI for AI Implementation

Due to the PCA, it was found that the factors that determine the readiness of companies operating in the energy sector industry to implement AI are the factor of economic efficiency, information security and correctness, legal regulation, professional training, psychological readiness, personnel development, and objectivity of decision-making. The Kaiser criterion determines the number of significant factors. The factor composition was determined based on the significant factor loadings of the indicator from the relevant factor. Significant factor loadings are taken $\geq |0.75|$ [114]. During the study period of 2018–2020, the factor composition for Russian and French enterprises is unchanged.

Cost efficiency is formed from the indicators AI_{17}, AI_{20}, AI_{21}, AI_{26}, AI_{30}, AI_{32}–AI_{39}, AI_{45}, which assess AI's ability to replace human labor with increased productivity, production efficiency, transportation, energy-saving, production volumes, improved product quality, and optimization of business processes. All indicators, except AI_{30}, AI_{39}, AI_{45}, are stimulators in assessing readiness to develop OI for AI implementation. Indicators AI_{30}, AI_{39}, AI_{45} reflect possible economic losses when using AI, which are:

- Increased unemployment and, as a consequence, decreased consumer demand;
- The high cost of AI implementation.

Negative factor loadings of these indicators are indicative of positive values of factor loadings of other factor indicators.

The information security factor, correctness, and legal regulation are composed of indicators AI_{13}, AI_{15}, AI_{16}, AI_{27}, AI_{31}, AI_{42}–AI_{44}. This readiness factor reflects the risks associated with the possibility of cyber-threats, data leak, system failure, lack of regulation at the legislative level of AI use, distribution of responsibility, and copyrights. The factor is a disincentive as its development reduces the readiness to develop OI for AI implementation.

The professional training factor reflects the level of education, computer skills, and experience in using AI in professional activities, creating an objective basis for AI implementation. The indicators that composed the factor were AI_9–AI_{11}, AI_{40}, AI_{41}.

The psychological readiness factor includes indicators AI_{12}, AI_{14}, AI_{28}, AI_{29}; it reflects the personal inclination of representatives of business leaders to risk and innovation, which are associated with AI implementation; the efficiency of the vendor management system from the perspective of the possibility to increase personnel readiness to implement technological innovations.

The staff development factor is a disincentive one in AI development. It reflects possible risks associated with professional degradation of employees (AI_{22}), decrease in responsibility (AI_{23}), intelligence (AI_{24}), and creativity (AI_{25}).

The decision-making objectivity factor reflects such positive AI aspects, such as objectivity, validity, and non-corruption of decision-making (AI_{18}, AI_{19}).

The values of variance, which characterize the importance of the factors that determine the readiness to develop OI for AI implementation in the enterprises operating in the energy sector industry of Russia and France, are shown in Figure 2 and Table 3, respectively.

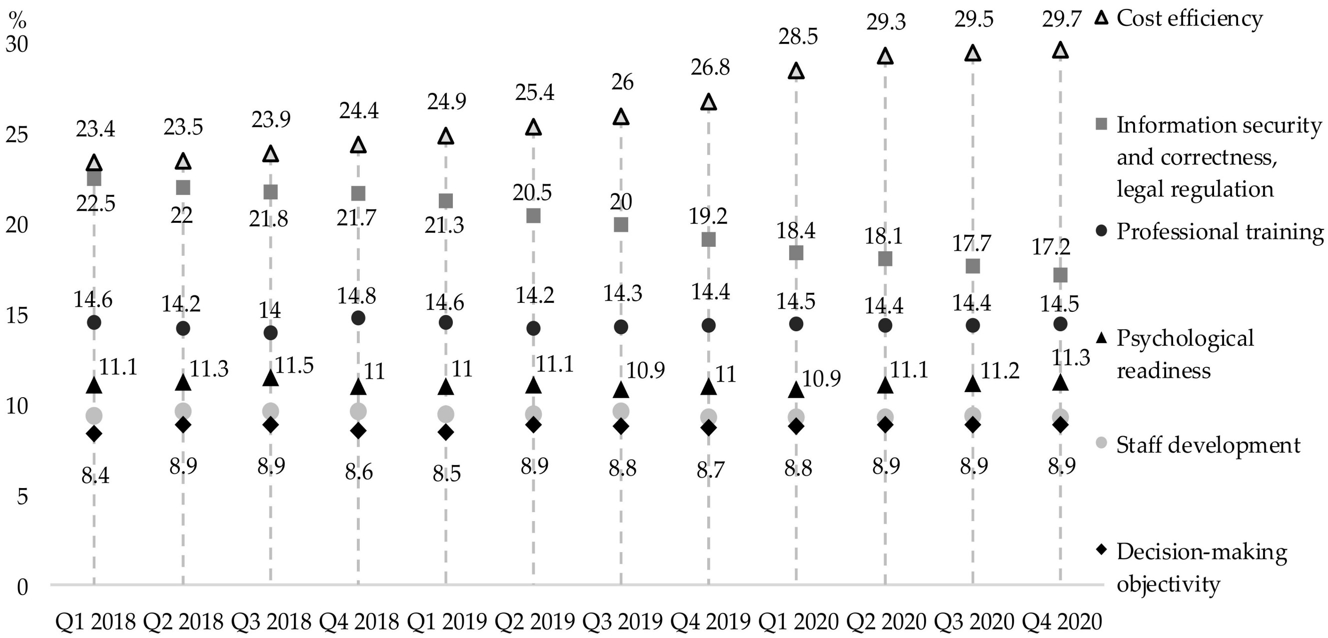

Figure 2. Variance factors determining the readiness of companies operating in the energy sector industry to develop OI for AI implementation in Russia.

Table 3. Factors determining the readiness of companies operating in the energy sector industry to develop OI for AI implementation in France.

Factor	Percentage of the Factor Variance by Survey Periods, %	
	February–June 2018	February–June 2018
Cost efficiency	24.8	26.7
Information security and correctness, legal regulation	17.7	17.0
Professional training	15.6	15.5
Psychological readiness	12.9	13.0
Staff development	10.5	10.2
Decision-making objectivity	9.4	9.6
Cumulative percentage of variance	90.9	92.0

The analysis showed that during the entire period, the most significant factor in assessing the readiness to develop OI for AI implementation, regardless of the country, is the factor of economic efficiency. Its variance has an upward trend over the study period: for Russia—from 23.4% to 29.7%, for France—from 24.8% to 26.7%. The importance of information security and correctness decreases from 22.5% to 17.2% in Russia and from 17.7% to 17% in France. It is associated with the continuous improvement of AI technologies and strengthening their information security. The importance of other factors is 14.0–15.6% for the training, 10.9–13.0% for psychological readiness, 9.3–10.5% for staff development, and 8.4–9.6% for the decision-making objectivity factors. The cumulative percentage of the variance 89.4–92.0%, which exceeds the 80% sufficient level [114], evidences the factor analysis adequacy.

4.3. Integrated Assessment of Readiness of Companies Operating in the Energy Sector Industry to Develop OI for AI Implementation

Using Fibonacci's sequence and Student's *t*-test, the ranges of indicator values, corresponding to the 100% confidence zone in attributing indicator values to a certain level, were determined based on assessments on questions nos. 9–45. The ranges of values are shown in Table 4.

Table 4. Value ranges of levels of indicators determining readiness to develop OI for AI implementation in Russian and French companies operating in the energy sector industry.

Indicator	Indicator Values by Level			Indicator	Indicator Values by Level		
	Low ($\mu_1 = 1$)	Medium ($\mu_2 = 1$)	High ($\mu_3 = 1$)		Low ($\mu_1 = 1$)	Medium ($\mu_2 = 1$)	High ($\mu_3 = 1$)
AI_9	[0; 3.6]	[4.0; 5.9]	[6.3; 10]	AI_{28}	[0; 1.4]	[2.0; 3.1]	[3.3; 5]
AI_{10}	[0; 1.5]	[2.1; 2.6]	[3.1; 5]	AI_{29}	[0; 1.7]	[2.3; 3.0]	[3.2; 5]
AI_{11}	[0; 5.5]	[5.8; 9.0]	[9.4; 15]	AI_{30}	[0; 1.6]	[2.0; 2.8]	[3.2; 5]
AI_{12}	[0; 1.8]	[2.0; 3.0]	[3.2; 5]	AI_{31}	[0; 1.2]	[1.9; 2.6]	[3.1; 5]
AI_{13}	[0; 1.7]	[1.9; 3.1]	[3.4; 5]	AI_{32}	[0; 1.7]	[2.0; 2.8]	[3.1; 5]
AI_{14}	[0; 1.8]	[2.0; 2.9]	[3.2; 5]	AI_{33}	[0; 1.6]	[1.9; 2.7]	[3.1; 5]
AI_{15}	[0; 1.8]	[2.1; 2.9]	[3.3; 5]	AI_{34}	[0; 1.8]	[2.1; 2.8]	[3.2; 5]
AI_{16}	[0; 1.6]	[1.9; 2.7]	[3.1; 5]	AI_{35}	[0; 1.7]	[2.1; 3.0]	[3.3; 5]
AI_{17}	[0; 1.7]	[2.0; 2.8]	[3.2; 5]	AI_{36}	[0; 1.8]	[2.0; 2.9]	[3.2; 5]
AI_{18}	[0; 1.5]	[2.2; 2.9]	[3.4; 5]	AI_{37}	[0; 1.6]	[2.0; 3.0]	[3.3; 5]
AI_{19}	[0; 1.7]	[2.1; 3.0]	[3.3; 5]	AI_{38}	[0; 1.8]	[1.9; 2.9]	[3.2; 5]
AI_{20}	[0; 1.6]	[2.4; 3.0]	[3.2; 5]	AI_{39}	[0; 1.8]	[2.0; 2.9]	[3.2; 5]
AI_{21}	[0; 1.8]	[2.4; 2.9]	[3.4; 5]	AI_{40}	[0; 1.5]	[2.1; 2.6]	[3.1; 5]
AI_{22}	[0; 1.9]	[2.0; 3.1]	[3.3; 5]	AI_{41}	[0; 1.8]	[2.4; 2.8]	[3.3; 5]
AI_{23}	[0; 1.6]	[2.0; 2.8]	[3.3; 5]	AI_{42}	[0; 1.6]	[2.0; 2.9]	[3.1; 5]
AI_{24}	[0; 1.6]	[2.2; 2.8]	[3.2; 5]	AI_{43}	[0; 1.8]	[2.0; 2.7]	[3.0; 5]
AI_{25}	[0; 1.5]	[2.1; 2.6]	[3.1; 5]	AI_{44}	[0; 1.5]	[2.0; 2.7]	[2.9; 5]
AI_{26}	[0; 1.8]	[2.0; 2.8]	[3.2; 5]	AI_{45}	[0; 1.6]	[2.1; 2.6]	[3.0; 5]
AI_{27}	[0; 1.7]	[2.1; 3.0]	[3.3; 5]				

The probability of attributing values, not included in the specified ranges to a certain level, was determined by the formula (1). The values of the readiness indicators to implement AI and their levels for the last studied period (Q4 2020 for Russia and February–June 2020 for France) are shown in Figure 3.

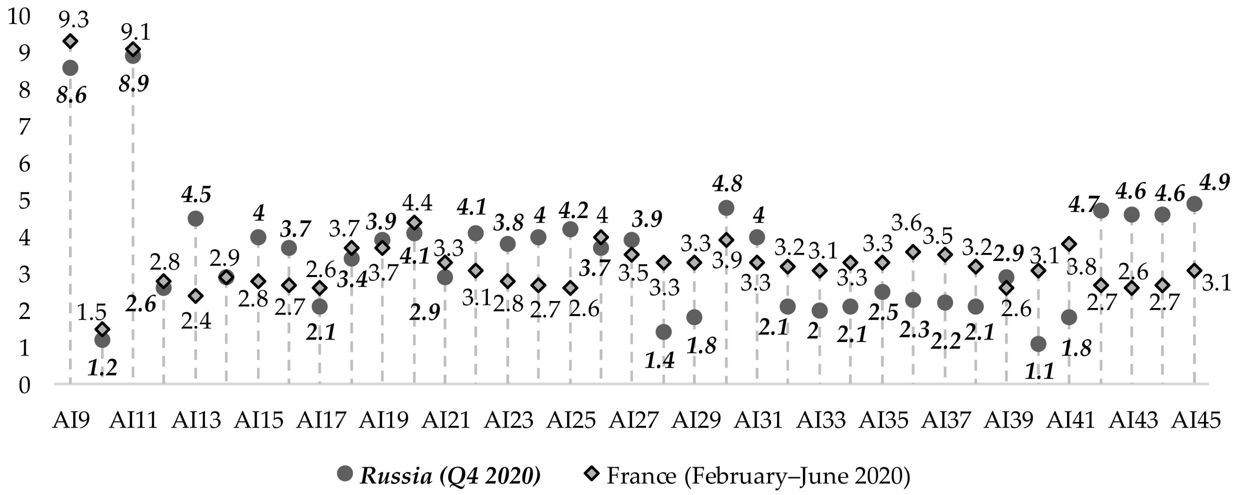

Figure 3. Values of readiness indicators of companies operating in the energy sector industry to develop OI for AI implementation in Russia and France.

The results of the survey in Russia have shown a high level of indicator that stimulates OI development for AI implementation. It is the level of education—the majority of respondents have a master's degree, and some have a bachelor's degree. Business representatives positively assess the ability to increase objectivity and validity in decision-making with the use of AI (the average indicator value is 3.4 points out of 5), reduce corruption (3.9 points), reduce the time spent on work tasks (4.1 points), increase business efficiency (3.7 points). At the same time, along with awareness of the economic efficiency of AI technology, respondents point to the high cost of these technologies (4.9 points out of 5).

Disincentives in AI development are the low information security, correctness, legal regulation, and the professional training factors due to the legislative lack of AI functioning regulation and the lack of experience of its application by employees. In contrast to middle and senior management, the psychological readiness factor is low for employees and lower-level managers, which indicates a low degree of perception of technological innovations.

In terms of individual indicators, there is a high risk of cyber threats (4.5 points out of 5), risk of data leak (4 points), wrong decision making (3.7 points), professional degradation of employees (4.1 points), loss of employees' ability to make decisions and take responsibility (3.8 points), a decrease of employees' intelligence (4 points) and creativity (4.2 points), creation of a fake reality (3.9 points), significant growth of unemployment (4.8 points), failure in the functioning of AI technologies (4 points), low level of AI user experience in professional activity (1.1 points), and high risks associated with legislative misregulation (4.6–4.7 points). A significant disincentive in OI development for AI implementation is also an ineffective vendor management system, which does not involve a motivation to use AI technologies and psychological work to increase the willingness of personnel to use technological innovations. The ineffective vendor management system is evidenced by the average value of the indicator AI_{28} = 1.4 points in Russia. The destabilizing effect of this indicator is intensified by the negative personnel attitude to technological innovations (AI_{29} = 1.8 points).

For enterprises in France, the readiness to develop OI for AI implementation is higher in all components. It is achieved by more user experience in AI technology, more trust in AI, and awareness of its cost-efficiency. The higher readiness rates are also due to legislative regulation in the use of AI: defining decision-making responsibilities [116], prioritizing cooperation of European Union countries for AI development [117–121].

The dynamics of the integrated indicator of readiness to develop OI for AI implementation of companies operating in the energy sector industry, calculated by the formula (2), is shown in Figure 4. The table shows the average values of the integrated indicator for the sample of respondents and their levels. Low readiness level for AI implementation corresponds to values of the integrated indicator (0.1; 0.35), average—(0.40; 0.59), high—(0.62; 0.9). The probability of attributing intermediate values to a certain level is determined by the formula (1) by analogy with the classification of individual readiness indicators of companies to develop OI for AI implementation.

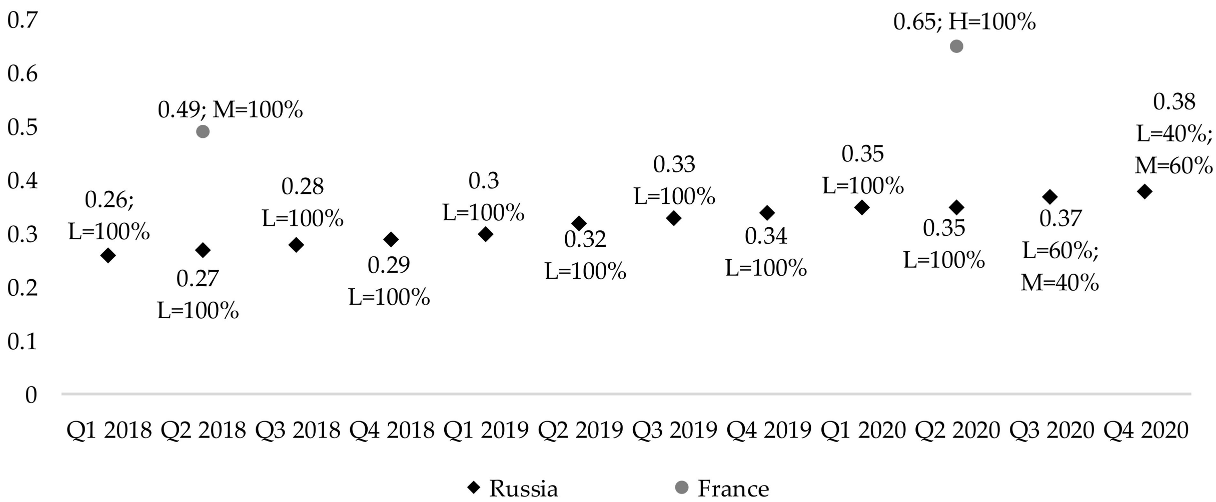

Figure 4. Values and levels of the readiness integrated indicator to develop OI for AI implementation of Russian and French companies operating in the energy sector industry. Note: L—the probability of assigning the value of the integrated readiness indicator to develop OI for AI implementation to the low level; M—to the medium; H—to the high level.

The analysis shows that the readiness level to develop OI for AI implementation has a pronounced upward trend over 2018–2020 in two countries. Despite this, readiness to implement AI in Russia was at a low level until Q2 2020 inclusive. In Q3 2020, readiness was classified as low, with a probability of 60%, and as a medium with a probability of 40%. In Q4 2020, it is possible to assert with 60% confidence the medium level of readiness and with 40%—the low level. While maintaining these integrated indicator growth rates, Russian companies will be ready to implement AI in 3–4 years, when the readiness indicator reaches a high level.

In France, the readiness to develop OI for AI implementation was at an average level in 2018 and a high level in 2020, with integrated indicator values of 0.49 and 0.65. Despite the high level of readiness, according to the survey results in 2020, the disincentives in AI development in France are the high cost of technology, higher risk of fake reality creation, failure of AI technology functioning, and unemployment growth in the country.

5. Discussion

5.1. The Efficiency of AI Technologies Implementation in the Energy Sector: The Implication of OI

The Energy sector in 2019–2021 years has to cope with an ever-increasing demand for energy and pressure from regulators and consumers to improve services, conserve exhaustible natural resources, and reduce carbon emissions. Only a rapid and high-quality modernization of the power grid using AI technologies and OI can reduce the impact of these factors on energy companies' business. For example, the International Energy Agency (IEA) estimates that AI technologies will save more than 5% of power generation costs [9,122]. This is why the industry, which invested only in rare capital IT projects for many years, is now investing billions of dollars in innovations. Gartner estimates that there are already more than 1.1 billion smart devices in power grids worldwide, and their number is growing rapidly. This is because detectors and sensors connected to the grid can collect and transmit all information needed for the stable work of the power grid. Already, drones and IoT devices are being used to check facilities and lines in hard-to-reach areas, and smart meters provide up-to-the-minute data on electricity demand. Moreover, IoT sensors also help monitor sudden changes in temperature, humidity, vibration, and many other parameters that affect grid overloads and power outages. This helps reduce the risks of power grid malfunctions. Another technology that is already fundamentally changing the principles of the energy sector is the digital twin [123]. This is a virtual copy of the energy system, which reliably displays the state of all physical assets of the energy company. Data from sensors, cameras, and other sources of information located at each infrastructure object are transmitted in real time to a specialized information system and used to create its exact three-dimensional model. The result is an environment with one source of reliable information about all company's assets. Availability of a virtual copy of a physical asset makes it possible to test maintenance methods, simulate equipment operation scenarios, train employees, and analyze safety measures without having to interfere with real, often expensive, facilities. Digital twins are especially useful during equipment maintenance scheduling and construction of new facilities. For example, Volgogradnefteproekt created a digital twin in the process of designing a large-scale gas processing complex. As a result of the project, it was possible to optimize the construction and operation of the new facility and reduce potential downtime by 10–15%. Total savings from the use of the twin are estimated at USD 5.5 million. Studies show that the digital twin market will grow by 58% per year until 2026, with a significant share of revenues coming from energy companies [124].

Decarbonization, power distribution, and the transition to RES can cause additional fluctuations in power supply. Therefore, electric grid operators today face problems related to ensuring the stability and reliable operation of the power grid more often than ever before. Any accident at a substation means thousands of people disconnected from power, financial and reputational damage to the company. Digitalization of the power grids and, in particular, the introduction of digital substations can increase the capacity of substations and increase their fault tolerance. Digital components such as IoT sensors, drones, cameras, and a wide range of analytical tools enable remote monitoring, diagnosis, and control of all equipment. As a result, substation management becomes completely transparent. This makes it possible to predict power system failures in advance and schedule all infrastructure facilities' maintenance. That is why the digital substation concept is rapidly gaining popularity. For example, there are more than 2 million smart metering devices, 84 digital substations, 22 grid control centers, and 38 digital electric grid districts in the perimeter of PJSC Russian Grids [125].

The growing decentralization of power systems makes it increasingly difficult to manage a large number of grid members. This requires analyzing a huge flow of data. AI is helping to process these flows in real time. Therefore, the energy sector is increasingly using machine learning and AI tools to improve energy efficiency, grid stability, energy forecasting and transparency of electricity trade, emergency and recovery management, and many other tasks. For example, National Grid in the United Kingdom uses Google's DeepMind to predict peaks in supply and demand and, as a result, reduce electricity consumption nationwide by 10%. Over time, there will be more and more scenarios for applying AI to the energy sector. Thus, domestic energy companies will be investing at least 10–20% of their IT budgets in projects based on AI in the coming years. Finally, another technology that helps efficiently manage the decentralized assets of energy companies is blockchain. A blockchain-based electricity sales system allows end customers to buy the product directly from energy companies. In doing so, energy companies can cut out the middlemen who charge for their services. In turn, electricity consumers get a convenient tool for making transactions quickly and safely [126]. In Bavaria, a platform is being tested by which energy companies will be able to sell electricity to local consumers without the involvement of power system operators [127].

Thus, it can be argued that energy companies that have long and actively applied the concept of OI in business are the most competitive and most efficient in implementing AI technologies.

5.2. Method for Assessing the Readiness of Companies Operating in the Energy Industry to Implement AI

A method was proposed for assessing the readiness of companies operating in the energy sector industry to implement AI, which differs by the presence of the integrated indicator and way of its calculation, as well as taking into account the need to implement an OI strategy as an essential condition for the AI use. The method of fuzzy sets, used to determine the integrated indicator and its levels, allows you to get a balanced assessment of all factors since the calculation of the integrated indicator takes into account not the absolute values of individual indicators, as in the methods [83], but their levels. Readiness to implement AI must be at the appropriate level for all factors since they are not interchangeable. For example, the lack of staff qualifications to use AI cannot be offset by the high efficiency of AI technologies without appropriate staff development activities. The high cost-efficiency of AI technologies cannot offset such a negative factor of AI implementation as the growth of unemployment without appropriate structural changes in the economy. When using the absolute values [83] in determining readiness to implement AI, high values of one indicator can mathematically compensate for low values of other indicators, which is excluded when using fuzzy sets.

The identified system of factors of readiness for OI development made it possible to identify the priority conditions that contribute to the active use of AI technologies in the energy industry of Russia and those that have a destructive effect.

The readiness of businesses to implement AI for OI development in the conditions of developed and developing markets differs significantly. Suppose the high cost is the main overall destructive factor of business readiness to implement AI technologies in France. In that case, the human factor is a significant obstacle in Russia, as the study showed. There is an insufficient number of relevant staff dealing with this type of innovation. It can also be explained by the objective dependence of their activities on other factors, which explains the lack of need for specialists to continuously monitor information about digital technologies, in particular about trends in AI. Given this, it is necessary to expand the capacity to train specialists in AI technology continuously. The level of theoretical research on AI in Russia is no lower than the world level. Besides, it should be noted that today Russia has sufficient potential in training qualified specialists for AI projects. According to the company «System Analysis and Program Development» (SAP) research, 286 universities have relevant master's programs, about 50,000 students study 65 specialties related to data analysis, machine learning, speech and image recognition, computer linguistics, etc. Over the past 5 years, more than 200,000 people have been trained in these programs [128]. Despite this, as an emerging market, Russia is significantly behind its global competitors in the number of scientific publications devoted to this technology. Therefore, it can be stated that the country should actively develop new specialties since AI technology application requires a much broader set of skills. Knowledge and skills in pure mathematics, computer science, data science, neurobiology, psychometry, behavioral psychology, linguistics, and other humanities will be necessary for learning and working with "smart" devices. This can only be solved by stimulating their employees to work closely with universities and research institutes, offering certain bonuses for advanced training in AI technology and data science through joint university programs, and so on.

One of the most significant obstacles to readiness for OI and AI technology of Russian companies in the energy sector is legislative misregulation. This spoiler can be explained by the gap of the theory of law to scientific and technological progress: the lack of legal regulation in the interaction between humans and AI, problems of morality, security, legal personality, responsibility, and privacy. Therefore, it becomes substantial to level down the legislative and administrative barriers to technological pioneering and implicitly ensuring the safety of the state and society. It is essential to adjust national legislation to the new technological reality to form a flexible, adequate legal framework for developing and using AI-based applications most quickly and qualitatively. It is also necessary to develop special regimes for private investment in creating breakthrough solutions and, of course, to guarantee reliable protection of intellectual property, legal conditions for the registration of patents in the national jurisdiction of Russia. It is necessary to develop AI standards at the national level and ensure their harmonization with international standards.

Neutralization of spoilers in the shortest possible time will make it possible to move from a low readiness level of companies operating in the energy sector industry to AI technologies to a high one. In turn, this will promote the widespread use of these technologies in the country, reducing Russia's gap in AI development with the leading countries, will stimulate the development of the industry and improvement of its efficiency, significant economic growth in the country in terms of life expectancy, the economic activity of the population, and production of goods with high added value.

The approach to assessing the readiness degree of companies to implement AI (list of evaluation indicators, data processing, and calculation methods of the integrated indicator) is universal and applicable to all branches of the economy regardless of the country and business development level. The limitation in this aspect is the need to recalculate the variance of the factors depending on the country and the branch, indicator levels underlying the integrated readiness indicator calculation.

6. Conclusions

This article seeks to add a new dimension to literature at the intersection of OI and AI in the energy market, which is actively moving toward the concept of EaaS, which implies providing new energy services directly to the consumer. EaaS includes consumption management, consumption optimization upon the availability of a local source and battery, energy exchange through the local grid, or energy savings. In this regard, energy companies that efficiently use innovative technologies and AI tools will more quickly gain a higher energy sector share.

The existing skills of enterprise staff in Russia do not allow the efficient use of OI and AI technology to solve its daily tasks. Moreover, there is resistance to innovation at different levels of the organization structure, hindering the efficient use of AI and the digital transformation of the enterprise. The main problem is a psychological factor: employees' fears that AI will contribute to job cuts at the enterprise, mental unreadiness to change, and unwillingness to learn. This evidences again about information vacuum in the benefits of AI technology in business. Therefore, the task of the national government is to communicate the positive prospects of Industry 4.0 to the population and, for business leaders, to use advanced Change Management technologies so that the majority of the population will be confident that robotics, digitalization, and automation will lead to new well-paying jobs requiring higher skills.

This study is of practical importance because, using Russia as an example, it makes it possible to econometrically determine the underlying destructive factors of readiness to develop OI for AI implementation in the practice of energy companies. This approach considers the specifics of development and the current state of energy companies that already use AI to improve business efficiency. The approach to assessing the degree of readiness of businesses to implement AI for OI development (list of evaluation indicators, methods of data processing, and calculation of the integrated indicator) is universal and applicable to all economies, regardless of the country's development level and business. The limitation in this aspect is the need to recalculate the variance of the factors depending on the country and the levels of indicators underlying the calculation of the integrated readiness indicator.

The results of this study are based only on a sample of two countries, which does not allow their implementation in the practice of the energy sectors in other countries.

However, due to significant features of the readiness of energy companies to develop OI and implement AI considering the development level of the country's economy and human capital, it seems necessary to study the qualitative parameters of human resources for AI in the energy sector.

Thus, it can be argued that energy companies that have long and actively applied the concept of OI in business are the most competitive and most efficient in implementing AI technologies.

The study has confirmed the hypotheses and substantiated the impact of using the OI concept of the energy sector company on the readiness to implement AI technologies and their effectiveness.

Author Contributions: Conceptualization, M.V. and O.D.; data curation, M.V. and I.N.; formal analysis, M.P. and I.N.; investigation, M.V.; methodology, M.V. and O.D.; project administration, O.D.; resources, M.P.; software, N.K.; supervision, O.D.; validation, N.K.; visualization, N.K.; writing—original draft, L.V.; writing—review and editing, E.K. and M.I. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Publicly available datasets were analyzed in this study. This data can be found here: [https://www.oxfordinsights.com/government-ai-readiness-index-2020] (accessed on 11 June 2021).

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

Appendix A

Table A1. Examples of applications of artificial intelligence in the energy sector [2,87–106].

Method	Executing Task	Some Examples
Neural networks	Weather forecasting	In the US state of Colorado, energy provider Xcel uses AI algorithms to process information from the "National Center for Atmospheric Research" (including satellite data in wind farm areas). This allows the company to generate detailed reports and optimize wind farm operations.
	Electrical power quality assessment with voltage measurement classification	
	Short term forecasting of energy consumption in buildings	
	Optimizations of operating modes of batteries backing up RES	
Machine learning	Optimizations of Microgrid and photovoltaic panels	Together with the US Department of Energy, IBM is implementing the SunShot initiative, in which a self-learning program can reliably predict the output of renewable sources (solar, wind, and hydro). The algorithm uses a large amount of retrospective data along with real-time weather monitoring information. The Spanish company Nnergix generates short- and medium-term forecasts (from 6 h to 10 days) of renewable generation using machine learning algorithms. London-based Green Running Ltd. is developing Verv, a machine-learning-based app designed to optimize the energy consumption of homes. The app works on computers, tablets, and smartphones. US-based Verdigris Technologies has developed software to optimize the energy consumption of commercial buildings with sensor-equipped spaces. Using this software to optimize the kitchen at the W Hotel San Francisco over three months, the company identified the causes and eliminated USD 13,000 worth of inefficient energy consumption (annualized). Individual offers to consumers based on smart metering data (Energy Lab der ETH Zürich).
	Predicting RES generation	
	Optimization of energy consumption	
	Location of electrical grid faults	
	Improvement of indoor comfort with accompanying energy optimization	
	Investigation of solar cell materials concerning their properties	
	Energy statistics and monitoring	
	Asset Performance Management (APM)	
	Energy trading	
	Optimization of hydro-power plants	
	Customer communications	

Table A1. *Cont.*

Method	Executing Task	Some Examples
	Oil and gas industry	The German company Schleswig-Holstein Netz AG, which operates the electrical grids in Schleswig-Holstein, is using a self-learning network to locate suspected faults. It uses information about the age of the network components, repairs made, loads, and weather conditions as input data. Processing geo-information data from the Swiss authority Bundesamt für Landestopografie (swisstopo) allows the state of energy infrastructure to be recognized, forecasting production, and so on. Origami Energy uses machine learning to predict market prices in real time. GE's equipment condition monitoring system (iCMS) has been used at the Pomt Baldy hydro-power plant (France) since December 2015 and has increased the plant's output by more than 1%. German energy group RWE uses the AI platform ITyX to handle customer inquiries, with 80% of incoming inquiries automatically analyzed and sorted by the platform. BP is investing in Beyond Limits, a start-up that uses machine learning to analyze images and geolocation models to improve the chances of successful drilling.
Deep learning	District heating network load forecasting Real-time forecasting of electrical grid losses Energy trading	The Austrian company Pöyry uses this technology to support trading and decision-making.
Enhanced training	Optimization of energy consumption Optimization of hydraulic systems operation	DeepMind Technologies Ltd., founded in London in 2010 and acquired by Google in 2014, has reduced the power consumption of Google's data center by 40%. Operation parameters of the center, equipped with thousands of sensors, were optimized by a neural learning network
Fuzzy logic	Optimization of hydraulic systems operation The optimal choice of sites for small hydro-power plants Optimizing operation of an electrostatic precipitator at a thermal power station Fuzzy logic relays for power transformer protection Fuzzy method for determining power flow distribution on harmonic frequencies Optimization of the choice of electrical grid configurations Management of artificial lighting during daylight hours Selection of installation place and power of capacitor banks	In cooperation with the University of Wrocław in Poland, ABB has developed a multi-criteria fuzzy logic-based protective relay for use with three-phase power transformers. The relay test results show high selectivity and sensitivity, with an average tripping time of less than half a cycle. The reliability of the relay has also been confirmed. In Germany, at the Voerde OHG coal-fired power plant of Evonik Steag GmbH and RWE Power AG, the modernization of the electrostatic precipitators has resulted in a sustainable reduction in energy consumption. The companies reduced operating costs and environmental impacts and increased the entire system efficiency due to optimization using the fuzzy logic software Winpic. A method based on fuzzy logic and expert systems to improve the efficiency of biofuel power plants have been successfully tested in five agricultural biogas units with combined heat and power production located in the German state of Bavaria.
Support vector machine	Application of the support vector machine in combination with fuzzy logic and genetic algorithms for detecting non-technical power losses in electric power grids	
Expert systems	Improving the efficiency of a biogas power plant using fuzzy logic and expert systems	

References

1. Abbate, T.; Codini, A.P.; Aquilani, B. Knowledge co-creation in open innovation digital platforms: Processes, tools and services. *J. Bus. Ind. Mark.* **2019**, *34*, 1434–1447. [CrossRef]
2. Cohen, A. Get Smart: AI and the Energy Sector Revolution. Forbes. 2020. Available online: https://www.forbes.com/sites/arielcohen/2020/08/31/get-smart-ai-and-the-energy-sector-revolution/?sh=5e5a25266044 (accessed on 15 October 2020).
3. Alvarez-Aros, E.L.; Bernal-Torres, C.A. Open innovation model: Focus on human potential. *Inf. Tecnol.* **2017**, *28*, 65–76. [CrossRef]
4. Mogilenko, A.V. Artificial Intelligence: Methods, Technologies, and Applications in the Energy Sector. Analytical Review. 2019. Available online: https://in.minenergo.gov.ru/analytics/iskusstvennyy-intellekt-metody-tekhnologii-primenenie-v-energetike-analiticheskiy-obzor (accessed on 18 February 2021).
5. Egorov, M. Top 5 Innovations in the Energy Sector: From the Internet of Things to Smart Grids. IKS-MEDIA. 2019. Available online: https://www.iksmedia.ru/articles/5584620-Top5-innovacij-v-energetike-ot-inte.html (accessed on 18 February 2021).
6. Data Economy. Artificial Intelligence and Its Role in Economic Transformation: Priority Sectors and Development Directions. Analytical report. n.d. Available online: https://data-economy.ru/survey_ai_202003 (accessed on 18 February 2021).

7. Kagermann, H.; Winter, J. Industrie 4.0 and platform-based Business Model Innovations (Industrie 4.0 und plattformbasierte Geschäftsmodellinnovationen). In *Handbook Industrie 4.0*; Lucks, K., Ed.; beck-eLibrary.DIE FACHBIBLIOTHEK: Stuttgart, Germany, 2017; pp. 21–32. Available online: https://www.beck-elibrary.de/10.34156/9783791038520-21/3-industrie-4-0-und-plattformbasierte-geschaeftsmodellinnovationen-henning-kagermann-und-johannes-winter (accessed on 18 February 2021). [CrossRef]
8. Stanford University. Artificial Intelligence and Life in 2030. 2016. Available online: https://ai100.stanford.edu/sites/default/files/ai100report10032016fnl_singles.pdf (accessed on 11 February 2021).
9. Lee, M.; He, G. An empirical analysis of applications of artificial intelligence algorithms in wind power technology innovation during 1980–2017. *J. Clean. Prod.* **2021**, *297*, 126536. [CrossRef]
10. Boza, P.; Evgeniou, T. Artificial intelligence to support the integration of variable renewable energy sources to the power system. *Appl. Energy* **2021**, *290*, 116754. [CrossRef]
11. Frost & Sullivan. Impact of Artificial Intelligence (AI) on Energy and Utilities, 2018. 2018. Available online: https://go.frost.com/NA_PR_JBrinkley_ME1F_AIEnergyUtilities_Dec18 (accessed on 15 October 2020).
12. Lv, Z.; Chen, D.; Lou, R.; Alazab, A. Artificial intelligence for securing industrial-based cyber–physical systems. *Future Gener. Comput. Syst.* **2021**, *117*, 291–298. [CrossRef]
13. Russian Association for Electronic Communications. Digital Economy from Theory to Practice: How Russian Business Uses Artificial Intelligence. 2020. Available online: https://raec.ru/activity/analytics/11002/ (accessed on 18 February 2021).
14. Oxford Insights. AI Readiness Index 2020. 2021. Available online: https://www.oxfordinsights.com/government-ai-readiness-index-2020 (accessed on 15 October 2020).
15. Abdulov, R. Artificial intelligence as an important factor of sustainable and crisis-free economic growth. *Procedia Comput. Sci.* **2020**, *169*, 468–472. [CrossRef]
16. Tatarkin, A. Innovation direction of the avarage region development in the modernization of the Russian Federation. *J. Contemp. Econ. Issues* **2013**, *3*. [CrossRef]
17. Gunyakov, Y.; Gunyakov, D. Restructuring and innovative business. *J. Contemp. Econ. Issues* **2013**, *2*. [CrossRef]
18. Seamans, R. *AI, Labor, Productivity and the Need for Firm-Level Data*; National Bureau of Economic Research: Cambridge, MA, USA, 2018.
19. International Data Corporation. Worldwide Spending on Artificial Intelligence Is Expected to Double in Four Years, Reaching $110 Billion in 2024, According to New IDC Spending Guide. 2020. Available online: https://www.idc.com/getdoc.jsp?containerid=prus46794720 (accessed on 15 October 2020).
20. TASS. More than 80% of the World's Energy COMPANIES Will Implement Artificial Intelligence by 2025. 2020. Available online: https://www.ruscable.ru/news/2020/11/27/Bolee_80_energokompanij_v_mire_vnedryat_iskusstven/ (accessed on 18 February 2021).
21. Eprussia. Energy Production is "Provided" with Intelligence to Only a Tenth of It. 2020. Available online: https://www.eprussia.ru/news/base/2020/9284128.htm (accessed on 15 October 2020).
22. Mousavizadeh, A.; Mostrous, A.; Clark, A. The Global AI Index. Tortoise Media. 2019. Available online: https://www.tortoisemedia.com/2019/12/03/global-ai-index/ (accessed on 15 October 2020).
23. Ahmad, T.; Zhang, D.; Huang, C.; Zhang, H.; Dai, N.; Song, Y.; Chen, H. Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities. *J. Clean. Prod.* **2021**, *289*, 125834. [CrossRef]
24. President of Russia. Decree of the President of the Russian Federation of 10.10.2019 no. 490. "On the Development of Artificial Intelligence in the Russian Federation". 2019. Available online: http://www.kremlin.ru/acts/bank/44731 (accessed on 15 October 2020).
25. Russia Data Economy. AI and Its Role in the Transformation of the Economy: Priority Sectors and Trends. 2020. Available online: https://ict.moscow/research/iskusstvennyi-intellekt-i-ego-rol-v-transformatsii-ekonomiki-prioritetnye-otrasli-i-napravleniia-razvitiia/ (accessed on 15 October 2020).
26. Statista. Projected Artificial Intelligence Spending in Europe in 2019 and 2023. 2020. Available online: https://www.statista.com/statistics/1115464/ai-spending-europe/ (accessed on 15 October 2020).
27. Al-Duhaidahawi, H.M.K.; Abdulreza, J.Z.S.; Sebai, M.; Harjan, S.A. An efficient model for financial risks assessment based on artificial neural networks. *J. Southwest Jiaotong Univ.* **2020**, *55*. [CrossRef]
28. Utomo, D.T.; Pratikto, P.B.S. Preliminary study of web based decision support system to select manufacturing industry suppliers. *J. Southwest Jiaotong Univ.* **2020**, *55*. [CrossRef]
29. Deloitte. International Trends in Renewable Energy Sources. 2018. Available online: https://www2.deloitte.com/content/dam/Deloitte/ru/Documents/energy-resources/Russian/global-renewable-energy-trends.pdf (accessed on 15 October 2020).
30. Ministry of Energy of the Russian Federation. *Energy Strategy of Russia for the Period Up to 2030*; Institute of Energy Strategy: Moscow, Russia, 2010; Available online: http://www.energystrategy.ru/projects/docs/ES-2030_(Eng).pdf (accessed on 19 March 2021).
31. Deloitte. Energy Supply as a Service. *The Lights Are on. Is Anyone Home? 2019*. Available online: https://www2.deloitte.com/content/dam/Deloitte/ru/Documents/energy-resources/Russian/energy-as-service-ru.pdf (accessed on 18 February 2021).
32. Vella, H. Energy-as-a-Service Will Transform the Sector. 2019. Available online: https://www.raconteur.net/energy/energy-as-a-service/ (accessed on 19 March 2021).

33. Soni, N.; Sharma, E.K.; Singh, N.; Kapoor, A. Artificial intelligence in business: From research and innovation to market deployment. *Procedia Comput. Sci.* **2020**, *167*, 2200–2210. [CrossRef]
34. Fan, J.; Fang, L.; Wu, J.; Guo, Y.; Dai, Q. From brain science to artificial intelligence. *Engineering* **2020**, *6*, 248–252. [CrossRef]
35. Haefner, N.; Wincent, J.; Parida, V.; Gassmann, O. Artificial intelligence and innovation management: A review, framework, and research agenda. *Technol. Forecast. Soc. Chang.* **2021**, *162*, 120392. [CrossRef]
36. Bag, S.; Pretorius, J.H.C.; Gupta, S.; Dwivedi, Y.K. Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities. *Technol. Forecast. Soc. Chang.* **2020**, 120420. [CrossRef]
37. Lytras, M.D.; Visvizi, A. Artificial intelligence and cognitive computing: Methods, technologies, systems, applications and policy making. *Sustainability* **2021**, *13*, 3598. [CrossRef]
38. Faúndez-Ugalde, A.; Mellado-Silva, R.; Aldunate-Lizana, E. Use of artificial intelligence by tax administrations: An analysis regarding taxpayers' rights in Latin American countries. *Comput. Law Secur. Rev.* **2020**, *38*, 105441. [CrossRef]
39. IEEE-USA. Artificial Intelligence Research, Development & Regulation. 2017. Available online: https://insight.ieeeusa.org/wp-content/uploads/2017/07/FINALformattedIEEEUSAAIPS.pdf (accessed on 11 February 2021).
40. Semin, A.N.; Ponkratov, V.V.; Levchenko, K.G.; Pozdnyaev, A.S.; Kuznetsov, N.V.; Lenkova, O.V. Optimization model for the Russian electric power generation structure to reduce energy intensity of the economy. *Int. J. Energy Econ. Policy* **2019**, *9*, 379–387. [CrossRef]
41. Trofimov, V.V. Artificial Intelligence in the Digital Economy. The Roscongress Foundation. 2019. Available online: https://roscongress.org/materials/iskusstvennyy-intellekt-v-tsifrovoy-ekonomike/ (accessed on 25 May 2021).
42. Barrett, D.H.; Haruna, A. Artificial intelligence and machine learning for targeted energy storage solutions. *Curr. Opin. Electrochem.* **2020**, *21*, 160–166. [CrossRef]
43. Chesbrough, H.W. *Open Innovation: The New Imperative for Creating and Profiting from Technology*; Harvard Business School Press: Boston, MA, USA, 2003.
44. Chesbrough, H.W. *Open Business Models: How to Thrive in the New Innovation Landscape*; Harvard Business School Press: Boston, MA, USA, 2006.
45. Ottonicar, S.L.C.; Arraiza, P.M.; Armellini, F. Opening science and innovation: Opportunities for emerging economies. *Foresight STI Gov.* **2020**, *14*, 95–111. [CrossRef]
46. Chesbrough, H.W. *From Open Science to Open Innovation*; Escola Superior d'Administració i Direcció d'Empreses: Barcelona, Spain, 2015.
47. Ayris, P.; Bernal, I.; Cavalli, V.; Dorch, B.; Frey, J.; Hallik, M.; Hormia-Poutanen, K.; Labastida, I.; MacColl, J.; Ponsati-Obiols, A.; et al. *Liber Open Science Roadmap*; Association of European Research Libraries: The Hague, The Netherlands, 2018. [CrossRef]
48. Harison, E.; Koski, H. Applying open innovation in business strategies: Evidence from Finnish software firms. *Res. Policy* **2010**, *39*, 351–359. [CrossRef]
49. Khovalova, T.V. Innovations in the electric power industry: Types, classification and effects of implementation. *Strateg. Decis. Risk Manag.* **2019**, *10*, 274–283. [CrossRef]
50. Binghai, Z.; Zhexin, Z. Dynamic scheduling of material delivery based on neural network and knowledge base. *J. Hunan Univ. Nat. Sci.* **2020**, *47*, 1–9.
51. Chen, J.; Zhao, X.; Wang, Y. A new measurement of intellectual capital and its impact on innovation performance in an open innovation paradigm. *Int. J. Technol. Manag.* **2015**, *67*, 1–25. [CrossRef]
52. Sagar, A.; Gallaher, K.; Holdren, J. Energy-technology innovation. *Annu. Rev. Environ. Resour.* **2006**, *31*, 193–237. [CrossRef]
53. Amponsah, C.T.; Adams, S. Open innovation: Systematisation of knowledge exploration and exploitation for commercialization. *Int. J. Innov. Manag.* **2017**, *21*, 1750027. [CrossRef]
54. Trachuk, A.V.; Linder, N.V. The Impact of technologies of the Industry 4.0 on increase of productivity and transformation of innovative behavior of the industrial companies. *Strateg. Decis. Risk Manag.* **2020**, *11*, 132–149. [CrossRef]
55. European Commission. *Open Innovation, Open Science, Open to the World: A Vision for Europe*; Publications Office of the European Union: Luxembourg, 2016.
56. Faissal Bassis, N.; Armellini, F. Systems of innovation and innovation ecosystems: A literature review in search of complementarities. *J. Evol. Econ.* **2018**, *28*, 1053–1080. [CrossRef]
57. Govindarajan, V.; Kopalle, P.K. Disruptiveness of innovations: Measurement and an assessment of reliability and validity. *Strateg. Manag. J.* **2006**, *27*, 189–199. [CrossRef]
58. AltexSoft. Comparing Machine Learning as a Service: Amazon, Microsoft Azure, Google Cloud AI, IBM Watson. 2021. Available online: https://www.altexsoft.com/blog/datascience/comparing-machine-learning-as-a-service-amazon-microsoft-azure-google-cloud-ai-ibm-watson/ (accessed on 25 May 2021).
59. Ruffini, G. An algorithmic information theory of consciousness. *Neurosci. Conscious.* **2017**, *2017*, nix019. [CrossRef]
60. Veisdal, J. The Birthplace of AI. The 1956 Dartmouth Workshop. Medium. 2019. Available online: https://medium.com/cantors-paradise/the-birthplace-of-ai-9ab7d4e5fb00 (accessed on 15 October 2020).
61. Maslov, S. An inverse method of establishing deducibility in classical predicate calculus. *Proc. USSR Acad. Sci.* **1964**, *159*, 17–20.
62. Turchin, V.F.; Serdobol'skii, V.I. The refal language and its use in transforming algebraic expressions. *Cybernetics* **1969**, *5*, 307–312. [CrossRef]

63. Lyre, H. The state space of artificial intelligence. *Minds Mach.* **2020**, *30*, 325–347. [CrossRef]
64. Lee, J.; Davari, H.; Singh, J.; Pandhare, V. Industrial artificial intelligence for Industry 4.0-based manufacturing systems. *Manuf. Lett.* **2018**, *18*, 20–23. [CrossRef]
65. Massaro, M.; Rubens, A.; Bardy, R.; Bagnoli, C. Antecedents to export performance and how Italian and Slovanian SME's innovate during times of crisis. *J. East. Eur. Cent. Asian Res.* **2017**, *4*, 22. [CrossRef]
66. Osipov, G.; Karepova, S.; Chizhevskaya, E.; Gnatyuk, M.; Semin, A.; Mikhayluk, O. Directions to improve the effectiveness of Russia's energy export policy. *Int. J. Energy Econ. Policy* **2018**, *8*, 227–239. [CrossRef]
67. Kagermann, H.; Winter, J. The second wave of digitalization: Germany's Chance. In *Germany and the World 2030: What will Change, How We Must Act*; Mair, S., Messner, D., Meyer, L., Eds.; Econ Publishers: Berlin, Germany, 2019; pp. 201–209.
68. Wirth, N. Hello marketing, what can artificial intelligence help you with? *Int. J. Mark. Res.* **2018**, *60*, 435–438. [CrossRef]
69. Kim, D.; Shin, D.; Shin, D. Unauthorized Access Point Detection Using Machine Learning Algorithms for Information Protection. In Proceedings of the 17th IEEE International Conference on Trust, Security and Privacy in Computing and Communications/12th IEEE International Conference on Big Data Science and Engineering, New York, NY, USA, 1–3 August 2018; Institute of Electrical and Electronics Engineers: New York, NY, USA, 2018; pp. 1876–1878. [CrossRef]
70. Truong, T.C.; Diep, Q.B.; Zelinka, I. Artificial intelligence in the cyber domain: Offense and defense. *Symmetry* **2020**, *12*, 410. [CrossRef]
71. Loureiro, S.M.C.; Guerreiro, J.; Tussyadiah, I. Artificial intelligence in business: State of the art and future research agenda. *J. Bus. Res.* **2020**. [CrossRef]
72. Hitz, C.; Schwer, K. The role of IT governance in digital operating models. *J. Eastern Eur. Central Asian Res.* **2018**, *5*, 19. [CrossRef]
73. Schwer, K.; Hitz, C. Designing Organizational Structure In The Age Of Digitization. *J. East. Eur. Central Asian Res.* **2018**, *5*, 11. [CrossRef]
74. Ernst, E.; Merola, R.; Samaan, D. Economics of artificial intelligence: Implications for the future of work. *IZA J. Labor Policy* **2019**, *9*, 20190004. [CrossRef]
75. Di Vaio, A.; Palladino, R.; Hassan, R.; Escobar, O. Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review. *J. Bus. Res.* **2020**, *121*, 283–314. [CrossRef]
76. Toorajipour, R.; Sohrabpour, V.; Nazarpour, A.; Oghazi, P.; Fischl, M. Artificial intelligence in supply chain management: A systematic literature review. *J. Bus. Res.* **2021**, *122*, 502–517. [CrossRef]
77. Davenport, T.; Guha, A.; Grewal, D.; Bressgott, T. How artificial intelligence will change the future of marketing. *J. Acad. Mark. Sci.* **2020**, *48*, 24–42. [CrossRef]
78. Swankie, G.; Broby, D. Examining the Impact of Artificial Intelligence on the Evaluation of Banking Risk. Centre for Financial Regulation and Innovation. 2019. Available online: https://www.researchgate.net/publication/337908452_Examining_the_Impact_of_Artificial_Intelligence_on_the_Evaluation_of_Banking_Risk (accessed on 15 October 2020).
79. Calvo, R.A.; Peters, D.; Cave, S. Advancing impact assessment for intelligent systems. *Nat. Mach. Intell.* **2020**, *2*, 89–91. [CrossRef]
80. Nortje, M.A. *An Enterprise Technology Readiness Model for Artificial Intelligence*; Stellenbosch University: Stellenbosch, South Africa, 2020.
81. Bostrom, N. *Superintelligence: Paths, Dangers, Strategies*; Oxford University Press: Oxford, UK, 2014.
82. Kurzweil, R. The singularity is near. In *Ethics and Emerging Technologies*; Sandler, R.L., Ed.; Palgrave Macmillan: London, UK, 2014; pp. 393–406. [CrossRef]
83. McKinsey & Company. Artificial Intelligence: The Next Digital Frontier? 2017. Available online: https://www.mckinsey.com/~{}/media/mckinsey/industries/advanced%20electronics/our%20insights/how%20artificial%20intelligence%20can%20deliver%20real%20value%20to%20companies/mgi-artificial-intelligence-discussion-paper.ashx (accessed on 15 October 2020).
84. The European Parliament. The Ethics of Artificial Intelligence: Issues and Initiatives. 2020. Available online: https://www.europarl.europa.eu/RegData/etudes/STUD/2020/634452/EPRS_STU(2020)634452_EN.pdf (accessed on 15 October 2020).
85. Pangea Strategic Intelligence. AI Investment Opportunities. 2021. Available online: https://www.pangea-si.com/ai-investment-opportunities/ (accessed on 15 October 2020).
86. Mogilenko, A.V. Application of artificial intelligence algorithms in the global energy sector. *Energy Ind. Russia* **2018**, *13–14*, 345–346.
87. Greco, M.; Locatelli, G.; Lisi, S. Open innovation in utilities. *Energy Policy* **2017**, *104*, 316–324. [CrossRef]
88. Galus, M.; Grigorie, M.; Hertach, M.; Holzner, C. Digitalisierung im Energiesektor: Dialogpapier zum Transformationsprozess. 2018. Available online: https://www.newsd.admin.ch/newsd/message/attachments/55402.pdf (accessed on 18 February 2021).
89. Saha, M.M.; Hillström, B.; Kasztenny, B.; Rosolowski, E. A fuzzy logic based relay for power transformer protection. *ABB Tidning* **1998**, *1*, 41–48.
90. Conte, F.; Dinkel, F.; Stettler, C. Entscheidungshilfe für Die Ökologische Standortwahl von Schweizer Kleinwasserkraftwerken. 2017. Available online: https://www.aramis.admin.ch/Default?DocumentID=65530&Load=true (accessed on 18 February 2021).
91. Whittaker, M.; Crawford, K.; Dobbe, R.; Fried, G.; Kaziunas, E.; Mathur, V.; West, S.M.; Richardson, R.; Schultz, J.; Schwartz, O. AI Now Report 2018. AI Now Institute. 2018. Available online: https://ainowinstitute.org/AI_Now_2018_Report.pdf (accessed on 18 February 2021).

92. Viernstein, L. Einsatz neuronaler Netze zur Kompensation von Kommunikationsausfällen im Speicherbetrieb. 2018. Available online: https://www.tugraz.at/fileadmin/user_upload/Events/Eninnov2018/files/pr/Session_E6/PR_Viernstein.pdf (accessed on 18 February 2021).
93. Faber, T.; Groß, J.; Finkenrath, M. Innovative Lastprognosen mit »Deep Learning«-Methoden. 2018. Available online: https://www.hs-kempten.de/fileadmin/Forschung/Forschungsprojekte/Dokumente_projekte/DeepDHC_EuroHeat___Power_2018_1-2-18_S._35-38.pdf (accessed on 18 February 2021).
94. Hock, K.P. Real-Time loss Prediction. T&D World. 2018. Available online: https://www.tdworld.com/grid-innovations/distribution/article/20971883/realtime-loss-prediction (accessed on 18 February 2021).
95. Libisch-Lehner, C. Evolutionary multi-objective direct policy search (EMODPS), eine heuristische Entscheidungshilfe in der Wasserwirtschaft. In 15. Symposium Energieinnovation, Graz, Austria, 15 February 2018. Available online: https://www.tugraz.at/fileadmin/user_upload/Events/Eninnov2018/files/pr/Session_C3/PR_Libisch-Lehner.pdf (accessed on 18 February 2021).
96. Sokratherm. Contracting fuer Die Gesundheit. 2011. Available online: https://www.sokratherm.de/wp-content/uploads/bwk-7-8-2011.pdf (accessed on 18 February 2021).
97. Masoum, M.A.S.; Fuchs, E.F. *Power Quality in Power Systems and Electrical Machines*, 2nd ed.; Elsevier: Amsterdam, The Netherlands, 2015.
98. Working Group on Losses Reduction. Reduction of Technical and Non-Technical Losses In Distribution Networks; 2017. Available online: http://www.elder.org.tr/Content/makale/CIRED%20WG%202015-2%20Losses%20Final%20REPORT.PDF (accessed on 18 February 2021).
99. Djatkov, D.; Effenberger, M.; Martinov, M. Method for assessing and improving the efficiency of agricultural biogas plants based on fuzzy logic and expert systems. *Appl. Energy* **2014**, *134*, 163–175. [CrossRef]
100. GE Renewable Energy. *Hydropower's Digital Transformation, Ecomagination*; GE Renewable Energy: Paris, France, 2017.
101. Adamer, S. Ressourceneinsparung durch Künstliche Intelligenz. Informationsdienst Wissenschaft. 2017. Available online: https://idw-online.de/de/news681422 (accessed on 18 February 2021).
102. Satapathy, P.; Dhar, S.; Dash, P.K. An evolutionary online sequential extreme learning machine for maximum power point tracking and control in multi-photovoltaic microgrid system. *Renew. Energy Focus* **2017**, *21*, 33–53. [CrossRef]
103. Ma, L.; Ma, Y.; Lee, K.Y. An intelligent power plant fault diagnostics for varying degree of severity and loading conditions. *IEEE Trans. Energy Convers.* **2010**, *25*, 546–554. [CrossRef]
104. Kahraman, C.; Kaymak, U.; Yazici, A. *Fuzzy Logic in Its 50th Year: New Developments, Directions and Challenges*; Springer International Publishing: Cham, Switzerland, 2016. [CrossRef]
105. Ribeiro, P.F.; Duque, C.A.; da Silveira, P.M.; Cerqueira, A.S. *Power Systems Signal Processing for Smart Grids*; John Wiley & Sons Ltd.: Hoboken, NJ, USA, 2014.
106. Atabekov, A.; Yastrebov, O. Legal status of artificial intelligence across countries: Legislation on the move. *Eur. Res. Stud. J.* **2018**, *21*, 773–782. [CrossRef]
107. Morgan, F.E.; Boudreaux, B.; Lohn, A.J.; Ashby, M.; Curriden, C.; Klima, K.; Grossman, D. *Military Applications of Artificial Intelligence: Ethical Concerns in an Uncertain World*; RAND Corporation: Santa Monica, CA, USA, 2020. [CrossRef]
108. Kozyulin, V. Militarization of AI from a Russian Perspective. 2019. Available online: https://stanleycenter.org/wp-content/uploads/2020/05/MilitarizationofAI-Russia.pdf (accessed on 15 October 2020).
109. Bashkatova, A. AI Is Not Interesting for Domestic Business. Independent Newspaper. 2017. Available online: https://www.ng.ru/economics/2017-05-24/100_intellect240517.html (accessed on 15 October 2020).
110. Nugroho, M.A. Impact of government support and competitor pressure on the readiness of SMEs in Indonesia in adopting the information technology. *Procedia Comput. Sci.* **2015**, *72*, 102–111. [CrossRef]
111. Nugroho, M.A.; Susilo, A.Z.; Fajar, M.A.; Rahmawati, D. Exploratory study of SMEs technology adoption readiness factors. *Procedia Comput. Sci.* **2017**, *124*, 329–336. [CrossRef]
112. Questionnaire for Assessing the Readiness to Implement AI of Companies Operating in the Energy Sector Industry. Available online: https://docs.google.com/forms/d/1tR-xrTbq5RtbFlrlW0xen_Q9quMounZykpmNqXGf_ZE/viewform?edit_requested=true (accessed on 6 June 2021).
113. Gokhberg, L.; Ditkovskiy, K.; Evnevich, E.; Kuznetsova, I.; Martynova, S.; Ratay, T.; Rosovetskaya, L.; Fridlyanova, S. *Indicators of Innovation in the Russian Federation: 2020: Data Book*; National Research University Higher School of Economics: Moscow, Russia, 2020; Available online: https://issek.hse.ru/mirror/pubs/share/397986230.pdf (accessed on 11 February 2021).
114. Menke, W. Factor Analysis. In *Geophysical Data Analysis*, 4th ed.; Academic Press: New York, NY, USA, 2018; pp. 207–222.
115. Krawczak, M.; Szkatuła, G. On matching of intuitionistic fuzzy sets. *Inf. Sci.* **2020**, *517*, 254–274. [CrossRef]
116. European Parliament. European Parliament Resolution of 16 February 2017 with Recommendations to the Commission on Civil Law Rules on Robotics (2015/2013(INL). 2017. Available online: https://www.europarl.europa.eu/doceo/document/TA-8-2017-0051_EN.html (accessed on 15 October 2020).
117. European Union. EU Declaration on Cooperation on Artificial Intelligence. 2018. Available online: https://ec.europa.eu/jrc/communities/en/node/1286/document/eu-declaration-cooperation-artificial-intelligence (accessed on 15 October 2020).
118. European Commission. Communication Artificial Intelligence for Europe. 2018. Available online: https://ec.europa.eu/digital-single-market/en/news/communication-artificial-intelligence-europe (accessed on 15 October 2020).

119. European Commission. Coordinated Plan on Artificial Intelligence. 2018. Available online: https://ec.europa.eu/digital-single-market/en/news/coordinated-plan-artificial-intelligence/ (accessed on 15 October 2020).
120. European Commission. Ethics Guidelines for Trustworthy AI. 2019. Available online: https://ec.europa.eu/digital-single-market/en/news/ethics-guidelines-trustworthy-ai (accessed on 15 October 2020).
121. European Commission. Policy and Investment Recommendations for Trustworthy Artificial Intelligence. 2019. Available online: https://ec.europa.eu/digital-single-market/en/news/policy-and-investment-recommendations-trustworthy-artificial-intelligence (accessed on 15 October 2020).
122. International Energy Agency. Attracting Private Investment to Fund Sustainable Recoveries: The Case of Indonesia's Power Sector. 2020. Available online: https://www.iea.org/reports/attracting-private-investment-to-fund-sustainable-recoveries-the-case-of-indonesias-power-sector (accessed on 19 March 2021).
123. Rasheed, A.; San, O.; Kvamsdal, T. Digital Twin: VALUES, Challenges and Enablers. 2019. Available online: https://arxiv.org/pdf/1910.01719.pdf (accessed on 19 March 2021).
124. Alvarez, V. Volgogradnefteproekt Creates Digital Twin of a Large-Scale Gas Processing Complex, Enabling Streamlined Design, Construction, and Operations, and Reducing Downtime by 10%–15%. Bentley. 2020. Available online: https://www.bentley.com/ru/about-us/news/2020/october/19/ai-volgogradnefteproekt (accessed on 19 March 2021).
125. Henderson, M.I.; Novosel, D.; Crow, M.L. Electric Power Grid Modernization Trends, Challenges, and Opportunities. Institute of Electrical and Electronics Engineers. 2017. Available online: https://www.ieee.org/content/dam/ieee-org/ieee/web/org/about/corporate/ieee-industry-advisory-board/electric-power-grid-modernization.pdf (accessed on 19 March 2021).
126. Rimsan, M.; Mahmood, A.K. Application of blockchain and smart contract to ensure temper-proof data availability for energy supply chain. *J. Hunan Univ. Nat. Sci.* **2020**, *47*, 154–164.
127. Disruptor Daily. Ultimate Guide to Blockchain in Energy. 2020. Available online: https://www.disruptordaily.com/ultimate-guide-to-blockchain-in-energy/ (accessed on 19 March 2021).
128. Tadviser. AI Research. 2019. Available online: https://www.tadviser.ru/index.php/%D0%A1%D1%82%D0%B0%D1%82%D1%8C%D1%8F:%D0%98%D1%81%D1%81%D0%BB%D0%B5%D0%B4%D0%BE%D0%B2%D0%B0%D0%BD%D0%B8%D1%8F_%D0%B2_%D1%81%D1%84%D0%B5%D1%80%D0%B5_%D0%B8%D1%81%D0%BA%D1%83%D1%81%D1%81%D1%82%D0%B2%D0%B5%D0%BD%D0%BD%D0%BE%D0%B3%D0%BE_%D0%B8%D0%BD%D1%82%D0%B5%D0%BB%D0%BB%D0%B5%D0%BA%D1%82%D0%B0#.D0.98.D1.81.D1.81.D0.BB.D0.B5.D0.B4.D0.BE.D0.B2.D0.B0.D0.BD.D0.B8.D0.B5_PwC_AI_Predictions (accessed on 15 October 2020).