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Artificial Intelligence to Predict Solar Energy Production: Risks and Economic Efficiency

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Abstract: In the context of sustainable development and the increasing shift to non-fossil alternative energy sources, solar energy offers countless advantages for its conversion into electricity. Modern technologies provide excellent opportunities for the introduction of artificial intelligence in the process of predicting the production of solar energy. However, this topic is still relatively unexplored in the international scientific community, which makes this study relevant. This study aims to analyse the impact of artificial intelligence on solar energy production forecasting. The method of this study was a systematic review. The search for sources was conducted in the Google Scholar, Springer Link, and EBSCO databases from 2019 to 2024, allowing for a focus on the latest publications. As a result of applying PRISMA guidelines, 18 publications that fully met the inclusion criteria were selected. As a result of the study, it was possible to establish that artificial intelligence has great potential for its implementation in forecasting solar energy production. The study established random prediction models and machine learning models based on artificial intelligence for their cost effectiveness and risk in forecasting solar energy production. During the literature review, it became clear that the following four models are the most effective in the work: the RFR, LIME, ELI5 and SHAP. Each model has its advantages and disadvantages. These are manifested in production management, forecasting with high speed, flexibility, and explanation, reducing the risk of variability. However, the cost-effectiveness of implementing artificial intelligence in forecasting solar energy production is much more economically efficient than the risk aspects.

Keywords: artificial intelligence, data analysis, energy efficiency, sustainable development, predictive algorithms, production optimization, renewable energy, solar energy.

Introduction

An important task in the current international conditions is the transition to alternative energy. Under the current conditions of climate change, the international society needs to replace fossil energy sources with non-fossil, renewable energy sources (Puri et al., 2019). Mughal et al (2022) found that technological innovation in the process of digitalization has an important place in successful sustainable economic development by reducing the burden on the environment and improving the energy of countries. Solar energy is an important alternative, sustainable, and environmentally friendly source that is gaining popularity every year (Hayat et al., 2019). In today's world, solar energy has become an important source of energy in the landscape, primarily due to its availability and environmental cleanliness (Rychka, 2024). Due to technological breakthroughs, the efficiency and affordability of solar energy systems have increased significantly over time. The introduction of artificial intelligence algorithms and processes is one of the key developments that have transformed the solar energy industry. Analyzing the challenges and opportunities of artificial intelligence in sustainable energy, Ahmad et al. (2021) concluded that big data, machine learning model development, and artificial intelligence will play an important role in future energy markets. Solar energy is no exception. Solar energy production can be maximized through the use of artificial intelligence to improve performance, efficiency, and overall system performance.

However, the problem is that despite all the listed achievements and advantages of using artificial intelligence in the solar energy production industry, it is not clear how effective such an implementation can be in the process of production forecasting, as well as what risks are associated with such an implementation.

Research Problem

As discussed in previous publications, it is important today to study the effectiveness of using artificial intelligence to predict solar energy production, as well as the risks associated with such a process, for two reasons (Antonopoulos et. al., 2020; Elsheikh et al., 2019). First, with digitization and the rapidly evolving industrial automation landscape, the emergence of Industry 5.0 heralds a paradigm shift in human-machine interaction in the coming years (Vogel-Heuser & Bengler, 2023). In the search for a balance in the human-machine relationship, there are better ways of working, including artificial intelligence in the solar energy industry (Elsaraiti & Merabet, 2022; World Customs Organization, 2019). Second, the topic touches on the important issue of improving the performance of alternative energy sources, which is important in today's conditions of constant climate change. Modern society is actively fighting climate change on the planet every year (Akhter et. al., 2019; AlKandari & Ahmad, 2020). The harmful effects of industry, fossil fuel emissions, increased energy consumption and human activities are worsening the climate situation worldwide. Today, society and the global economy are evolving by the UN Sustainable Development Goals, which the international community must achieve by 2030. Of the 17 goals, two are directly relevant to the problem at hand. UN Sustainable Development Goal 13 concerns climate change and urgent action to combat it. It is climate change that is negatively affecting the economies of various countries and the lives of people. UN Sustainable Development Goal 7 focuses on energy, namely energy affordability, renewable energy use, and energy intensity (Ditlev-Simonsen, 2022; Elavarasan et al., 2023; Thacker et al., 2019). Introducing the use of artificial intelligence in solar energy production forecasting can improve this process and make it more cost-effective (Runge & Zmeureanu, 2019). Solar energy forecasting is necessary for policy making, understanding the problems and continuous optimal integration of the right measures for efficient operation of energy production (Shamshirband et al., 2019; Sharadga et al., 2020).

Research Focus

First of all, the analysis aims to determine the risks and cost-effectiveness of implementing artificial intelligence in the process of forecasting solar energy production in practice. The analysis of such aspects will help to identify negative consequences and minimize their negative impact in practice during implementation.

Research Aim and Research Questions

The purpose of this research is to analyze the impact of artificial intelligence on the prediction of solar energy production. Therefore, the paper will address two research questions:

1. Is there a cost-effectiveness of implementing artificial intelligence for predicting solar energy production?

2. What are the risks of implementing artificial intelligence in the process of forecasting solar energy production?

Literature Review

In the international discourse, some researchers have raised the issue of using artificial intelligence to predict solar energy production (Ahmad et. al., 2022; Mellit et al., 2020). To date, much has been achieved in the field of solar energy with the help of artificial intelligence. Researchers Mohammad and Mahjabeen (2023) point out the benefits of introducing artificial intelligence into the solar power generation industry, such as improvements in grid integration of solar power, including grid stability, demand response, and load management. However, for the most part, such studies have focused on the advantages or disadvantages that artificial intelligence can provide in forecasting solar power generation. For example, Mazzeo et al. (2021) focused on the application of artificial intelligence to predict the performance of a clean energy community. As a result of the study, the researchers concluded that properly aligned technologies and the application of artificial intelligence and neural networks can lead to very high accuracy in predicting energy generated from alternative sources. Examining different methods of solar forecasting, Singla et al. (2021) found through a study that artificial intelligence-based models outperformed other models due to their nonlinear capabilities to solve complex problems. Exploring the future of renewable energy forecasting, Sweeney et al. (2020) point out that with current technology, it will be possible in the future to use artificial intelligence to forecast solar energy production minutes to days in advance. By analyzing the prediction of solar power generation using statistical methods and artificial intelligence, Sharadga et al. (2020) concluded that the prediction of power generation is crucial for safe grid operation, scheduling, and power system management. Compared to statistical forecasting methods, artificial intelligence-based methods are more accurate, but require more time to compute forecasts (Sharifi et al., 2021).

After analyzing the already conducted studies, we can conclude that they have some shortcomings. First of all, all studies differ in their methodological approaches, which makes it difficult to find the effectiveness of implementing artificial intelligence in the process of forecasting solar energy production. Second, the economic efficiency and risks of implementing artificial intelligence in the process of forecasting solar energy production are only indirectly mentioned in many studies, but are not the main subject of research. Therefore, it can be concluded that this is a research gap in the field of solar energy and artificial intelligence. Therefore, this study aims to fill this research gap.

Materials and Methods

In this study, the literature was analyzed using a systematic literature review. The systematic literature review is a research method that systematically examines and analyzes all the literature available on a particular topic or issue at the time of the study. This method was chosen because of its advantages over other methods of evaluating literature, such as meta-synthesis and meta-analysis. In the systematic literature review, there is no limitation on the sources analyzed, whereas meta-synthesis is used to evaluate qualitative studies based on qualitative reports and meta-analysis is used to evaluate quantitative studies (Xiao & Watson, 2019). In the context of this study, a systematic literature review has the greatest advantages: a wide range of topics are covered simultaneously with varying degrees of completeness; each section is easily reproducible and replicable; and specific research questions of the study are explored (Page et al., 2021; Sarkis-Onofre et al., 2021).

The study was conducted in three phases: Selection of topic, selection of articles to be analyzed, subsequent selection of articles, and review of selected literature on the research topic. These stages were performed sequentially to present the research process in a clearer and more structured manner (Linnenluecke et al., 2020).

In the first stage of research article preparation, in addition to identifying the research topic and formulating the research question, keywords for searching the necessary sources were identified and a plan for finding the necessary research was made. The terms "artificial intelligence", "production forecasting", "solar energy", and "alternative energy" were used as search terms to formulate the research question.

The second stage involved searching and selecting appropriate literature to fulfill the purpose of the study. Selection of online databases based on the specific institutional database and further review of literature based on the specific institutional database. The literature search was conducted from March to April 2024. The literature search is based on literature reviews and systematic literature analysis. The search strategy aims to cover the published literature in the searchable databases Google Scholar, Springer Link and EBSCO. For the final analysis of the systematic literature review, the articles were carefully read and the results were related to the research questions.

To ensure the representativeness of the research findings, criteria were identified to answer the research question. The inclusion and exclusion criteria for the literature review were defined as follows:

1. The studies and articles analyzed were published and reviewed. Non-reviewed articles were not included in the analysis.

2. Both literature reviews and systematic literature reviews were included.

3. The study period was from 2019 to 2024. Articles published before 2019 were not included in the analysis.

4. Studies that included information on the risks and cost-effectiveness of using artificial intelligence to predict solar energy production were included. Studies that did not provide enough of this detailed information were excluded.

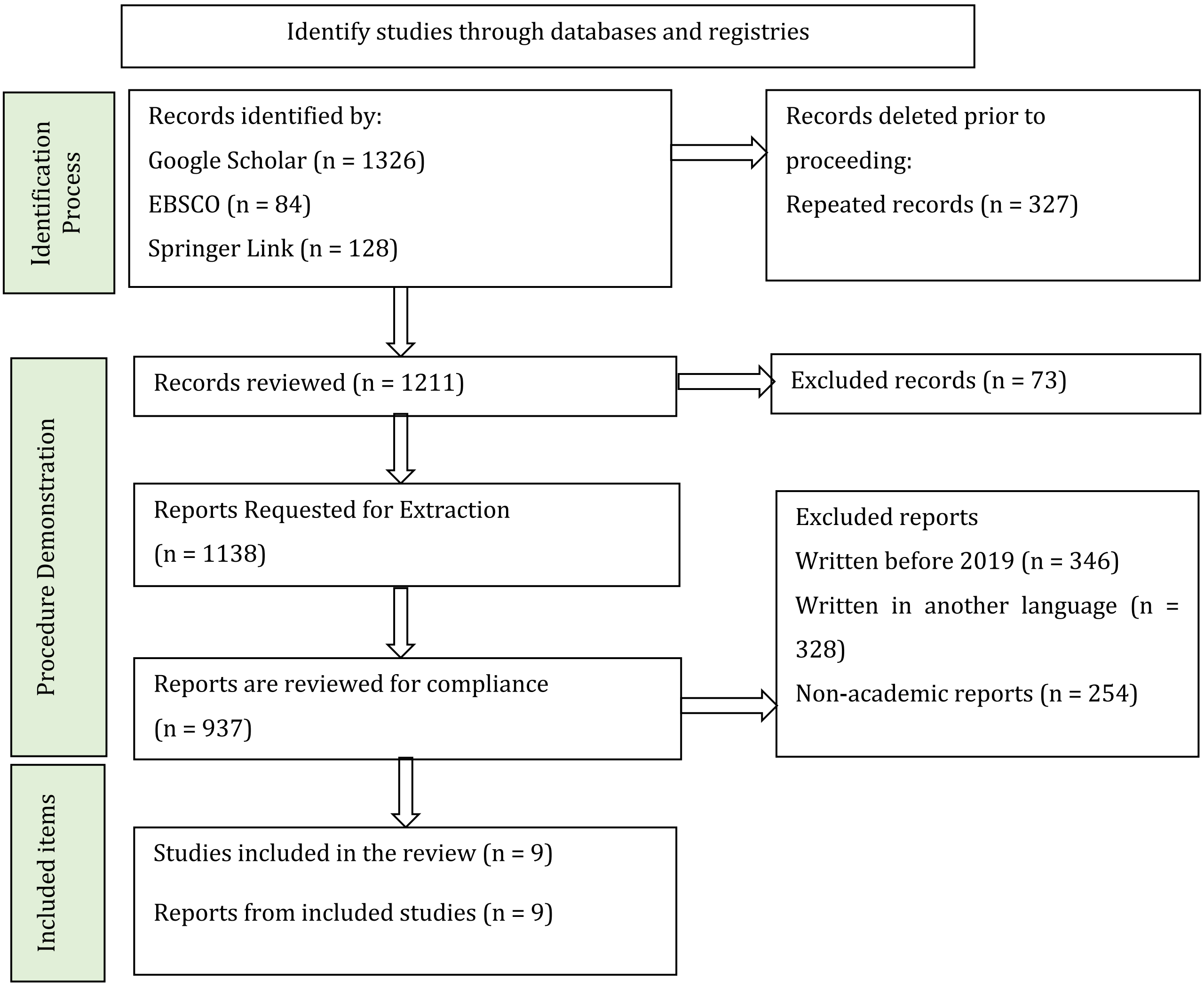
5. Articles were written in English. Articles written in other languages were excluded from further analysis.

Results

To analyze the research questions, keyword searches and Google Scholar, Springer Link, and EBSCO databases yielded 1538 hits (Figure 1).

Figure 1

Structure of the Study



Source: Authors' development.

For example, the Google Scholar search engine yielded 1326 hits, Springer Link yielded 128 hits, and the EBSCO database yielded 94 hits. Upon analysis, some studies were found to be duplicates. After removing the duplicates, 1,211 references remained. In addition, some articles did not contain a full report, so they were also excluded from further analysis. There were 73 such articles in the three databases at the same time. Some of these studies could not be extracted and retrieved, leaving a total of 201 sources. These records were then screened against the narrow research profile and the topic of this study, the inclusion criteria. This left 9 articles (Table 1).

Table 1

Articles Included in the Analysis

Author	Year	Country	Scientific basis	Methodology
Kuzlu et. al.	2020	USA, Norway	Google Scholar	Statistical Analysis
Anuradha et. al.	2021	India	EBSCO	Statistical Analysis

Del Ser et. al.	2021	Spain	EBSCO	Experimental study
Şerban and Lytras	2020	Saudi Arabia, Romania	Google Scholar	Literary Analysis
Al-Dahidi et. al.	2019	Jordan	Google Scholar	Statistical Analysis
Hannan et. al.	2021	Malaysia, Saudi Arabia, Australia	EBSCO	Literary Analysis
Doroshuk	2021	Ukraine	Google Scholar	Literary Analysis
Nallakaruppan et al.	2024	India, Norway, Lebanon, United Kingdom	EBSCO	Statistical Analysis
Mitrentsis and Lens	2022	Germany	Google Scholar	Statistical Analysis

Source: Author's development.

The main choice in determining the research design was to focus the research on the inductive method, which is appropriate within the framework of the ongoing work. The comparative method was used to study the problem and draw conclusions about the practical significance of the research conducted. Thanks to the abstract-logical method as a result of the work it was possible to conclude the whole study.

From a scientific point of view, any scientific article is considered a valuable source of information from which ideas can be drawn. For the final analysis, the articles were carefully read and correlated with the research questions in this systematic literature review. All full-text articles that met the eligibility criteria were reviewed for quality by the author of the article.

Articles for analysis were selected using a deductive method, formulated with theory and material in mind, conducted in stages, and revised during analysis. All full-text articles that met the inclusion criteria were included. The results of the study may be useful for making recommendations to improve the current situation. It can be concluded that the systematic literature search was the most appropriate method for this study due to its advantages and the fact that the process was carried out sequentially with a careful selection of articles.

This systematic review included 17 studies, of which 17 (100%) were published in peer-reviewed journals between 2019 and 2024. Almost half of them (67%) were recent studies (≥2021 years). Of the selected articles, 5 (56%) were statistical analyses, one study (11%) was experimental, and three (34%) were literature reviews. The authors' ideas and studies in an international context were considered.

When discussing the cost-effectiveness of implementing artificial intelligence in solar energy production forecasting, it is important to understand the nature of solar energy production forecasting. Solar energy is converted into electrical energy by photovoltaic cells. Installing such a system is quite expensive and requires a lot of upfront costs. At the same time, the payback period is quite low. This energy conversion is affected by many factors daily, including location, time of day, and weather conditions. Therefore, the process of predicting production is quite complex. Therefore, by implementing artificial intelligence in the process of predicting solar energy production, the main goal that engineers and researchers have is cost-effectiveness with accurate calculations and minimal risks (Anuradha et al., 2021).

Machine learning has two main categories of applications: regression and classification. Solar energy prediction requires the use of regression techniques (Anuradha et al., 2021). A systematic literature review was able to identify two methods that meet this criterion for implementation: machine learning models and explicable artificial intelligence tools (Kuzlu et al., 2020).

Machine learning models include Random Forest Regression (hereafter referred to as RFR) (Anuradha et al., 2021; Kuzlu et al., 2020). This model is a machine learning method used in supervised learning. RFR can be used for both classification and regression problems. Decision trees using this method can be trained with randomly selected input data. In this case, there can be multiple decision trees. In the process of predicting solar energy production, engineers can combine different predictions from multiple decision trees simultaneously (Del Ser et al., 2021). RFR can produce accurate results without the need for aggressive fine-tuning of model hyperparameters (Kuzlu et al., 2020). That is, such a model provides multiple solutions and combines all solutions into one. For example, it is applicable for different climatic conditions such as summer, rainfall, winter, etc. (Anuradha et al., 2021). Many researchers tend to believe that it is RFR that can give the most accurate prediction results, which in turn affects the cost-effectiveness of its implementation (Anuradha et al., 2021; Kuzlu et al., 2020).

The explicable tools of artificial intelligence include many methods so far, as this field is new to research. But among those methods that have cost-effectiveness in predicting solar energy production can be considered Local Interpretable Model-agnostic explanations (hereinafter referred to as LIME) and SHapley ADDITIVE exPlanation, as well as ELI5 (Kuzlu et al., 2020). Let us consider each of these models in more detail.

SHapley's ADDITIVE exPlanation (hereafter referred to as SHAP) is a model that uses coalitional game theory to determine how well each group (or coalition) of agents can succeed on its own. SHAP has a Python implementation that provides a tool for visualizing each feature and its importance. It also works with tree models from the Scikit-learn Python package. The SHAP value is the only method that provides a complete explanation and takes into account all possible predictions, e.g. using all possible combinations of input data. The SHAP value represents the contribution of a variable to the difference between the actual prediction and the backup prediction. SHAP can guarantee properties such as consistency and local accuracy. SHAP provides more detailed information and results such as visualization, explanation of multiple predictions, dependency and summary plots, and the importance of functions with SHAP values (Kuzlu et al., 2020). During the study.

LIME is a model for understanding and interpreting basic machine learning models while remaining model agnostic. LIME was introduced with the idea of approximating a machine learning model with an understandable model (Nallakaruppan et al., 2024). This is done locally because it is easier to understand and approximate complex machine learning models globally. LIME is faster than SHAP because calculating SHAP values is very time-consuming as it checks all possible combinations (Kuzlu et al., 2020; Nallakaruppan et al, 2024).

ELI5 is a Python package that aims to explain machine learning models in Python. ELI5 assigns weights to each feature to represent the importance of the feature in a machine-learning model. ELI5 is implemented for the most popular Python-based machine learning packages such as Scikit-learn, Keras, and XGBoost. Unlike LIME, ELI5 is model agnostic and has its implementation of XGBoost. ELI5 is the simplest tool for predicting solar energy production using artificial intelligence (Kuzlu et al., 2020).

Consequently, the cost-effectiveness of implementation can be determined as follows. Artificial intelligence methods can provide forecasts, recommendations and decisions regarding production (Hannan et al., 2021). It is the artificial intelligence models in today's environment that can represent the most cost-effective approach to forecasting with high speed, flexibility and explanations. That is, the main advantage and economic efficiency of artificial intelligence involvement is in production management (Şerban & Lytras, 2020).

Today and in the near future, artificial intelligence and methods based on it can play an important role in changing and optimizing the energy system and transforming it into a sustainable system with an intelligent foundation. However, today there is still a lack of complete understanding of how artificial intelligence can act in the energy system in the production of energy from solar energy (Kuzlu et al., 2020). This poses significant risks to its use. In turn, it is these risks that prevent the full-scale and international adoption of artificial intelligence in forecasting solar energy production. Many of the scientists point to the lack of understanding and inexplicability of the inner workings of artificial intelligence in this industry (Kuzlu et al., 2020).

First, it should be noted that a major risk of LIME, ELI5, and SHAP is the need for multiple estimates of the initial model (Kuzlu et al., 2020). This greatly complicates the forecasting process. However, Kuzlu et al. (2020) found that LIME does not guarantee a perfect distribution of effects. The use of artificial intelligence in predicting solar energy production reduces the risk of solar energy variability by predicting and identifying patterns, performing specific tasks without human instructions, and optimizing the decision-making process (Al-Dahidi et al., 2019; Şerban & Lytras, 2020).

Discussion

The systematic literature review confirmed the fact that artificial intelligence has a place in current solar power generation forecasting and will have a special place in future forecasting. This is also confirmed by the Lai et al. (2020) study. However, like any other innovation, the introduction of artificial intelligence into the operation of solar power generation forecasting has both efficiencies and risks, which was the aim of this study. However, the efficiencies are much higher than the risks. At the same time, the risks are minimal.

The study found that the RFR model is one of the most effective in the process of predicting solar energy production in both summer and winter. Such conclusions were reached by researchers from India (Anuradha et al., 2021). Such results were confirmed in a study by Meng and Song (2020). The researchers focused their study on the effectiveness of RFR in northern China. The study found that in winter in China, due to its ability to reduce the risk of overtraining by balancing decision trees, the proposed model achieves average absolute percentage errors of only 2.83% and 3.89% for clear and cloudy days, respectively. However, on days when the weather conditions are unusual, the prediction errors are relatively large. These are days when the weather is characterized by rain or snow.

Therefore, the analysis showed that the prediction of solar energy production is highly dependent on weather conditions. And any artificial intelligence model has a risk in this regard. Such results converge with the findings of Kim et al. (2019), who investigated the use of machine learning to predict solar energy production. As a result of the study, the researchers concluded that a two-step modeling process that links unannounced weather variables to announced weather forecasts is the most appropriate use case in practice. The random forest regression algorithm was found to perform best in this task. This is especially true when the forecasts are one day ahead.

Consequently, it can be argued that solar energy in interaction with artificial intelligence in a synergistic effect in the near future will be able to transform the energy industry, namely the process of production forecasting.

Conclusions and Implications

In this study, random prediction models and artificial intelligence-based machine learning models are analyzed for their cost effectiveness and risk in the process of predicting solar energy production. During the literature review, it became clear that the following four models are the most effective in performance: the RFR, LIME, ELI5 and SHAP. The study was able to establish that each tool has its own strengths and limitations in terms of computational cost, local/global explanation, feature weights, etc., which in turn affect the cost-effectiveness and risks. However, in general, the efficiency of implementing artificial intelligence is much higher than the risks associated with such an implementation.

The results of this study have both practical and scientific significance. The scientific significance is to improve the knowledge about the cost-effectiveness and risk of implementing artificial intelligence models in solar power generation forecasting. The practical significance of this study is that the results can be used by engineers and researchers working on power generation and load forecasting, as it will provide insight into the potential and availability of artificial intelligence in this industry.

Suggestions for Future Research

This paper confirms the relevance of the article, since the cost-effectiveness and risk of implementing artificial intelligence in predicting solar energy production is one of the most discussed topics in the international community. This demonstrates the need to better understand this topic and develop effective strategies and improvements. The broad scope of this research provides many avenues for further research. Based on this research paper, further research can be conducted based on the issues that remain unresolved. First, there is the issue of randomness and uncertainty, as the aspect of randomness can threaten the reliability of the models used for forecasting. Second, there is the issue of applying artificial intelligence to predict energy production from other alternative sources such as water, wind, or biomass.

This study is limited to solar energy. Thirdly, the data collection methods can be extended based on a critical evaluation of this work. A comprehensive qualitative study using expert interviews is appropriate. This is advisable because it is possible to include the opinions of experts who have experienced first-hand the implementation of artificial intelligence in the process of predicting solar energy production. Experts can provide opinions and experiences that have been truly tested. The results of such a study can help develop customized strategies to optimize the implementation of artificial intelligence in the solar power generation forecasting process. In addition, such a study may reveal some points that may have been overlooked in a systematic literature review. Analyzing all possible risks, it is reasonable to assume that manual intervention can minimize the negative impact on data performance. However, to be sure of this assertion, the following studies in this area are important.

This means that further research is needed to understand how all possible aspects may affect the improvement of strategies and tactics to improve the implementation of artificial intelligence with maximum economic benefits and to develop appropriate risk mitigation measures. In other words, it can be concluded that it is important to further develop this topic by improving methodological approaches to develop optimized strategies that are suitable for many stakeholders in an international context.

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Conflict of Interest

None.

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