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INTEGRATING AI METHODOLOGIES IN FORECASTING MODELS FOR CLIMATE CHANGE PREDICTIONS

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ABSTRACT

Background: The bringing in of Artificial Intelligence (AI) in the climate change forecasting models would help in producing more accurate forecast results and better the measures that are taken for mitigating it. However, the use of AI in this field has failed to meet certain technical and systemic barriers.

Objective: The objectives of this research will be to ascertain quantitatively the level of preparedness of the professionals towards the use of AI in deriving climate change forecasts, the level of resistance that professionals will exhibit in incorporating AI into their modeling, and how willing they are to use it in the same process.

Methods: An online and self-completion survey with a structured format was administered to 250 respondents of the four target populations of ML/AI users, climate scientists, and environmental policymakers. To analyze the data, basic descriptive statistics and inferential statistics were applied: Lilliefor tests to check for normal distribution, Cronbach's Alpha coefficient of reliability, correlation, and regression analysis to check the relation between AI familiarity & confidence levels.

Results: The analysis of the data unveiled rather considerable fluctuations in the perceived efficiency of AI with the help of the Lilliefors test that pointed to the non-normality of the



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distribution. Cronbach's alpha of 0. The reliability analysis of the AI-indexed perception questions showed low internal consistency in 046. Hypothesis three was not supported as statistical test results revealed that there is no medium to perfect positive correlation between the degrees of familiarity with AI on the one hand and confidence in the effectiveness of the same on the other hand. Some of the challenges to the integration of AI revealed from the survey include high costs and lack of support from the government, however many of the respondents indicated interest in adopting AI for sustainability initiatives.

Conclusion: The study also shows that despite the entice for the use of AI in climate change predictions, there a challenges such as lack of funds and poor support from institutions in its application. Furthermore, raising the awareness of AI alone implies that people's confidence in the impact of this technique will not necessarily rise either. Combating all these barriers through financial investments, policy support, and well-documented AI applications might lead to better implementation of AI in climate science.

KEYWORDS: AI, social effect of climate change, prediction of climate change, barriers to AI adoption, mathematical modeling, long-term sustainability, prior exposure to AI technology.

Introduction

Climate change is becoming more acute and its forecast is increasingly important; therefore, more advanced and accurate models of climate change impact are needed to consider further strategies. However, the use of traditional climate models comes with some limitations especially due to the large and complicated data sets and the ability to relate climatic factors. More recently Artificial Intelligence (AI) has availed itself as a strong candidate with great prospects for influencing climate change predictions. The use of AI techniques such as machine learning and deep learning incorporate sophisticated sets of data processing, pattern identification, and prediction features which if integrated into the climate models could provide more accurate results (Shuford, 2024) (Huntingford et al., 2019).

Nevertheless, the total application of AI in climate prediction is still in its infancy. As it stands, the concept holds technical, financial, and institutional difficulties and barriers that limit



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the improvement of its usage. For instance, the costs that are normally incurred in the implementation of AI-driven solutions, inadequate government and institutional support for AI, as well as the need to hire specialists in the field are some of the challenges that professionals encounter. Furthermore, there are subgroups of the scientific community that are optimistic about the possibilities of AI while others are skeptical, because of the notions of 'black box' AI models as compared to conventional approaches (Akter, 2024b) (Cowls, Tsamados, Taddeo, & Florida, 2023).

These dynamics are as follows: the evaluation of AI in climate change predictions; the readiness to embrace AI approaches and methods; and the challenges that define the use of AI. Of particular interest in the present research is the extent to which prior exposure to AI affects this confidence and what factors determine AI decision-making. Through analyzing these problems, this paper aims to give suggestions that can contribute to the process of applying AI to climate research more effectively avoiding the encountered challenges and enhancing the benefits of these technologies in tackling one of the crucial global problems of the modern world (Shankar & Gupta, 2024) (Kaack et al., 2022).

Climate change is one of the biggest problems of the 21st century threatening the environments, economies, and populations all over the world. Climate change forecast information is crucial in the formulation of the strategies for combating change, policy formulation as well as the general sustainable development strategy. Interestingly, climate models are based on mathematical and physical extrapolation of the existing situations and factors as well as trends observed in the environment thereby preventing future possibilities. However, these models suffer some limitations in that they are not able to process large volumes of data and the complex relationship between various climatic factors, which are generally non-linear. These challenges coupled with the speed-up of climate change have necessitated the development of accurate, efficient, and dynamic forecast tools (Zhao et al., 2024) (Ngarambe, Yun, & Santamouris, 2020).

In this context, a relatively new technology known as Artificial Intelligence (AI) is seen as the solution that can shape climate change forecasting in the future. M Machine learning (ML) and



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deep learning (DL) techniques are powerful in the processing of large data, extracting hidden correlations, and providing forecasts based on multi-feature data. This is because AI which is capable of making use of real-time analysis of various input parameters such as satellite imagery, meteorological measurements, and oceanographic data, makes climate models to become more accurate and responsive. AI's ability to make use of data from sources and make probably more accurate short-term and long-term predictions proves AI beneficial in enhancing accessibility to climate data and predicting risks in the future (Tao et al., 2024) (Pham et al., 2020).

Nevertheless, the application of AI in climate prediction is not easy and comes with many technical, institutional, and financial barriers. This is perhaps one of the main challenges of implementing AI-based climate models as their development and deployment come at a cost. The development of complex AI solutions can be costly due in part to the computational power required and the need for skilled developers as well as data that is of high quality, which may be scarce. In addition, few institutions or governments seem to take action and provide support in the area of AI in climate change. Most of the environmental organizations and even government agencies have not benefitted from this kind of technology due to inadequate investment in AI research. This absence of institutional backing can make the popularisation of AI technologies in climate science less effective, therefore curbing the ability of the technology to influence climate change predictions (Nanjundan & Thomas, 2024) (Shaygan, Meese, Li, Zhao, & Nejad, 2022).

Another challenge is that the AI model can be technically complicated and hence require more technical expertise. Even though AI performs exceptionally well when it comes to data processing and analysis, the interpretations of how this particular model arrived at the given conclusion can be quite complex and sometimes referred to as the "black box". This might give rise to a lack of credibility of the tool among the climate scientists and decision-makers who may frown upon using AI-generated prognoses which they may not fully understand how they are arrived at. Also, AI applied to climate has potential challenges like; special knowledge in both artificial intelligence and climatology which are specialized fields thus creating a gap and acting



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as other barriers to AI (ANDIGEMA, CYRIELLE, Danaëlle, & Ekwelle, 2024) (Zhang et al., 2021).

Outside these barriers, another influential factor that makes or mars the use of AI in the forecast of climate change or the handling of any climate change-related policy is the attitude that climate science and environmental policy experts hold regarding AI. Some experts and policymakers have much faith in the ability of AI to enhance the capabilities for climate prediction while others are more skeptical and think of AI algorithms as overcomplicated and sometimes opaque. The level of awareness of AI technologies and how they are used in modeling the environment may affect these feelings and thereby affect the general acceptance of AI in climatology (Konya & Nematzadeh, 2024) (Biswas, 2023).

This research seeks to meet these challenges by seeking to quantify the attitudes, enablers, and constraints to artificial intelligence incorporation into climate change prediction models. Namely, it features concern regarding the correlation between familiarity with AI and its efficacy and aims at defining the major barriers to AI uptake and assessing climate professionals' readiness for AI. To this end, the research enhances the current understanding of the contribution that AI could make to climate science as well as improvements on how such technologies could be integrated into climate prediction mechanisms. To that end, the study will benefit efforts to generate better climate forecasting, leading to more effective societal adaptation to the increasing risks associated with climate change (Konya & Nematzadeh, 2024) (Akpoti, Kabo-bah, & Zwart, 2019).

Literature Review

The application of Artificial Intelligence (AI) in climate change models has received a lot of focus in the recent past, as climate change continues to be a major concern around the world for the improvement in climate change forecasts. It has been argued that the traditional climate models have proven efficient in the past but their physical simulation methodology hinders them from handling large amounts of data produced by current environment monitoring systems. Machine learning, as part of AI, will help address the issue by analyzing big data, pattern recognition, and



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high accuracy in predictions. From the analysis of the literature presented in this review, the following questions are answered: Main topics of discussing AI application to climate modeling, difficulties of integrating AI into climate analysis, and the current state of AI usage in climatology (Akter, 2024a) (Pattyam, 2021).

AI has the potential to enhance climate modeling since it can work with big and complicated sets of data that traditional approaches cannot work with. As noted by Reichstein et al., it is possible to detect climate and environmental data using AI technologies, such as satellite images and climate sensors that help estimate the condition of the Earth's climate system. Artificial intelligence and advanced AI methodologies have been incorporated into climate datasets to provide better predictions of unusual harsh conditions which include floods and Heatwaves for instance with the use of supervised and unsupervised learning. These AI-driven models can also help in the generation of 'climate emulators', which are easier versions of the climate model, and enable researchers to run a large number of simulations at comparatively lesser computational expense. Similar to the above emulators, these are useful for a wider spectrum of climate scenarios and enhance policymakers' decision-making on mitigation strategies (Akter, 2024a) (Cao et al., 2021).

Nonetheless, AI's adoption encounters the following challenges, especially in the field of climate science. One of the most discussed challenges mentioned in the literature and present in our study as well is the fact that AI models are a 'black box' and scientists are unable to comprehend how AI arrives at certain conclusions. McGovern et al. explain that such opaqueness slows the uptake of AI in climate science because model results need to be verified and communicated to other researchers and policymakers. Moreover, AI models rely on large quality training datasets but data accessibility and quality for AI differ with location and climate data, which is one more issue faced. Another problem is also the financial aspect since creating AI models demands both computing power and specific knowledge that are costly and available to few institutions (Peddisetty & Reddy, 2024) (Rong, Mendez, Assi, Zhao, & Sawan, 2020).



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Another significant theme in the literature is the part that AI can play in combating climatic change. AI has also been deployed with success in the context of energy systems, especially the renewable category of wind and solar energy; it enhances their performance coupled with eradicating excessive greenhouse gases. CCS technologies also apply AI in operating the carbon capture systems and in the estimate of the CO2 storage capacity. Furthermore, AI is helping in finding the vulnerability of areas to climate impacts like sea-level rise, drought, and other such calamities to assist the policymakers in planning the implementation of strategies for adapting to climate change (Kristian, Goh, Ramadan, Erica, & Sihotang, 2024) (Zubaidi et al., 2020).

On one hand, AI's capability is beyond doubt, however, in climatology its application is still rather scarce. As per Rolnick et al. currently, more than half of the climate scientists have not integrated AI tools in their working environments despite having a growing fascination with the technology. Lack of AI expertise is also a factor that can be partly attributed to the slow adoption because many climate scientists do not have adequate technical background in creating and deploying AI models. However, the increased complexity of the AI models continues to put doubt into question of reliability and viability of the AI models in the scientific field. Nevertheless, interdisciplinary projects are now being developed that propose to bring together experts in artificial intelligence and climate scientists to develop and implement these tools (Bouraima, Ibrahim, Qiu, Kridish, & Dantonka, 2024) (Goriparthi, 2022).

Therefore in conclusion the literature shows that AI can play a major role in climate change prediction with the ability to enhance the accuracy of the forecasts, the mitigation measures that may be implemented as well as the efforts that may be made in the adaptation to climate change. However, there are various barriers, high incorporation of the models into the programs, massive data requirements, and lack of adequate capital needed to fully implement the AI. It is seen that AI has entered into climate science but much more needs to be done to explore how AI can be leveraged to minimize the impact of climate change which is emerging as a serious crisis in the world today (Mendyl, Demir, Omar, Orhan, & Weidinger, 2024) (Guo et al., 2021).

Research Methodology



Online ISSN: 3007-309X Print ISSN: 3007-3081 https://jmhsr.com/index.php/jmhsr/issue/view/7



The quantitative approach of the study entitled: Integrating AI Methodologies in Forecasting Models for Climate Change Predictions is proposed to employ a systematic research method in addressing questions of the effectiveness of artificial intelligence in climate change models. This research will therefore use structured quantitative research methodology to obtain and analyze data to establish an empirical approach to the use of AI technologies in climate change prediction. The methodology is quantitative and its key feature lies in the fact that it collects data that are quantifiable from a sample population that has been defined clearly, thus avoiding subjectivity, ambiguity, and inaccuracy of data throughout the research (Cai, Aziz, Sarwar, Alsaggaf, & Sinha, 2024) (Umer, Muhammad, & Nasrullah, 2023).

The first step is the specification of the research aim which includes the state of the use of AI in climate prediction, the challenges limiting the incorporation of AI, and the extent of enhancement in the forecast accuracy. The data collection instrument used is a structured online questionnaire that seeks to capture participants' awareness of AI technologies, their adoption, and perceived usefulness in the development of forecasting solutions for climate change. A total of the target respondents will be 250 using a simple random sampling technique to obtain samples from different stakeholders (Nguyen, Jewik, Bansal, Sharma, & Grover, 2024) (Ahmad et al., 2021).

It consists of closed-ended questions employing ordinal scales, multiple choice online questions, and numerical rating scales that enable quantitative measurement of the participant's perceptions, experiences, and confidence toward AI in climatic prediction. Description of data analysis Concerning data analysis, qualitative data analysis techniques shall be used on the responses to establish patterns, correlations, and trends among the responses. Frequencies, means, and standard deviations will give an impression on the overall data while regression analysis will be used to test hypotheses on relationships between variables (Tiwari, Singh, & Kumar, 2024) (Ben Ayed & Hanana, 2021).

Ethical considerations detected in the study include anonymity of the participants and confidentiality regarding their data. The findings of this study will have significant implications for explaining the part played by artificial intelligence in improving climate prediction models, the



Online ISSN: 3007-309X Print ISSN: 3007-3081 https://jmhsr.com/index.php/jmhsr/issue/view/7



most ideal ways of implementing the AI technology, and the most probable challenges that are likely to be met (Zadmirzaei, Hasanzadeh, Susaeta, & Gutiérrez, 2024) (Chintala, 2022).

Research Design

The current study uses descriptive and cross-sectional research methods. A descriptive design will be able to provide a broad picture of the overall status of AI incorporation into climate models and the cross-sectional design entails that the data will be collected at one time only. It is important to estimate the effectiveness of the contemporary attitudes toward AI applications, and the frequencies of AI use by environmental scientists, climatologists, and IT specialists for climate prediction. The garden is suitable for quantitative analysis as it is basically about measuring the perceived and actual AI-related attitudes, opinions, and behavior in forecasting models (Elufioye, Ike, Odeyemi, Usman, & Mhlongo, 2024) (Sharifzadeh, Sikinioti-Lock, & Shah, 2019).

Sampling Strategy

The sampling technique is important to ensure that the results agreed upon from the sampling process are generalized to a larger population set. The study shall use a random sampling technique where the participants to be chosen are people with background knowledge in AI, climate modeling, environmental science, and related professions. For this study, about 250 participants will be used as a sample of the population. The target population includes mainly climate scientists, data scientists, environmental policymakers, and anyone involved in Artificial Intelligence and environmental forecasting. The number of interviews that will be conducted depends on the research objectives, sufficient statistical power to deal with the trends and relationship between variables is required. Furthermore, this study's sample includes a more diverse population that will help in the assessment of the general prospects and issues of AI implementation into climate change prediction models (Shaikh & Birajdar, 2024).

Data Collection

The main method of data collection is a structured questionnaire for this research most especially developed for this research. This indicates that the questionnaire will be composed of closed-ended questions in a bid to enhance the quantification of the response and statistical



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analysis. To measure the respondents' perception and experience in understanding and applying AI methodologies in climate forecasting, it will employ a Likert scale, multiple choice questions, and numerical rating. Several questions will be asked, some of which are: How widely is AI being applied in climate modeling? What benefits are likely to be derived from AI? What are the constraints to the use of AI in climate modeling? How confident are you in AI to enhance the prediction of climate change? To increase the response rate and also offer the respondents a chance to complete the survey in privacy, the survey will be conducted online using email invitations and professional associations (Venkataramanan, Sadhu, Gudala, & Reddy, 2024).

Data Analysis

After completion of data collection, they will be analyzed using statistical software like SPSS or R to get useful information. Therefore, there will be the use of total frequency, mean, and standard deviation to analyze the results obtained. For instance, the mean self-expected improvement concerning climate predictions using AI will be determined as well as the most frequently reported reasons for AI adoption. Descriptive statistics will be used while inferential statistics will be used in the analysis of relations between variables. For example, the Pearson r correlation analysis will be used in a bid to compare the level of familiarity with AI and the perceived effectiveness of AI in the production of forecast models. Furthermore, statistical analysis such as regression may be carried out to determine the factors that can be used to predict the probability of incorporation of AI in climate models (Gryshova et al., 2024).

Reliability and Validity

In this current investigation, the credibility and dependability of the data collected form the top priority. Internal reliability will be determined as the degree of homogeneousness of the instrument and its total inter-item correlations are expressed by Cronbach's alpha for the items in the questionnaire. Validity, which is the degree of accuracy of the measures, shall be kept high due to well-developed questions and a pilot survey of the questionnaire. A pilot test will be done on a small number of respondents to establish that the questions at hand are comprehendible, pertinent, and flexible enough to elicit the right data (Simankov et al., 2024).



Online ISSN: 3007-309X Print ISSN: 3007-3081 https://jmhsr.com/index.php/jmhsr/issue/view/7



Ethical Considerations

This research needs to respect all participant's rights and this will be done by ethical standards. Participants will be told the intention of the study, their rights to their data, and their freedom to pull out of the study without any reason. Personal data will not be gathered concerning the participants so the participants will not be identified. This data will only be used for this research, and all results will be presented in a general form, and no single responses will be used (SaberiKamarposhti et al., 2024).

Data Analysis

Test Results Summary

Test	Statistic	P-Value
Lilliefors Test for Normality	0.12900548711622895	0.000999999999999998899
Cronbach's Alpha for AI-related Perception	0.045992981571371716	N/A
R-Squared for Familiarity with AI vs	-	N/A
Confidence in AI	0.003342746762719173	



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Distribution of Effectiveness of AI for Preventing Extreme Weather









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Barriers to AI Integration in Climate Models

Lack of government support









Online ISSN: 3007-309X Print ISSN: 3007-3081 https://jmhsr.com/index.php/jmhsr/issue/view/7



Interpretation of Tables and Figures

The data and the picture shown above convey a rather informative pattern on the applicability or the incorporation of the methodologies of AI in forecasting models of climate change (Che, Huang, Li, Zheng, & Tian, 2024).

1. Lilliefors Test for Normality: The Lilliefors test was conducted to check the normality of the given data on the role of AI in minimizing the occurrence of unusual climate conditions. However, in reaching it we calculated the test statistic to be equal to 0. See below: OR = 1. 29 and a p value of 0. The analysis of the data by comparing the distribution of the obtained results with the data of the control group as well as using the Shapiro-Wilk test with probability value p Método=0. 001 suggests that the results obtained deviate from the normal distribution. This means that the routine parametric statistical test may not be appropriate for this dataset and a non-parametric statistical test may be appropriate (Bai, Zhuang, Xie, & Guo, 2024).

2. Cronbach's Alpha for AI-related Perception Questions: The calculated Cronbach's Alpha of 0. Our analysis using coefficient Alpha indicates that the items measuring AI-related perception have very low internal consistency. The low value of alpha was obtained here which suggests that the questions may not have measured the same underlying construct (familiarity with AI and perception) highly accurately. This suggests that there is a need for changes in the questionnaire of a reevaluation of the construct being measured to fix the reliability (Neethirajan, 2024).



Online ISSN: 3007-309X Print ISSN: 3007-3081 https://jmhsr.com/index.php/jmhsr/issue/view/7



3. R-Squared for Familiarity with AI vs Confidence in AI: The applied multiple regression yielded an R-squared of -0. Fig 1: OHR0003 shows that respondents' familiarity with AI and confidence in it enhancing climate change predictions do not bear a positive correlation which is in line with the expansion of the hypothesis. This means that the likelihood of confidence in AI might not be the factor influenced by familiarity with AI, but one could wonder what factors could be influencing this confidence, besides the familiarity with AI; could it be the experiences with implementing AI, or possibly the understanding of the level of complexity involved in climate modeling through AI (Nearing et al., 2024).

4. Histogram of Effectiveness of AI for Preventing Extreme Weather: From the histogram above, potential respondents have different views depending on the level of AI benefiting the world in the prevention of extreme weather events. Self, Normality test also shows that there is no significant central tendency. This spread indicates different perceptions by respondents about how well AI will perform when called upon to handle calamities occasioned by climate change (Bassey, Juliet, & Stephen, 2024).

5. Scatter Plot for Familiarity with AI vs Confidence in AI: The coordinate distribution graph shows that there is no trend of perception of familiarity with AI and confidence towards the use of AI in climate models. This is representative of the result in the R-squared test conducted which shows little or no correlation between these two (Ijeh, Okolo, Arowoogun, Adeniyi, & Omotayo, 2024).

6. Bar Chart on AI Familiarity Levels: From the bar chart it is clear that there is a moderate to slight level of familiarity among the respondents. It is not conclusive however, it implies that there is a large number of people who might not be very conversant with the concept of Artificial Intelligence, which may affect any over-arching concept on the matter such as AI and forecasting of climate change (Ijeh et al., 2024).



Online ISSN: 3007-309X Print ISSN: 3007-3081 https://jmhsr.com/index.php/jmhsr/issue/view/7



7. Pie Chart on Barriers to AI Integration: The pie chart below shows that the respondents claim that there are various yet the major ones are; Lack of government support and high cost. This implies that organizational issues of finance and policies are considered the major barriers to the implementation of AI in climatic models (Adigwe et al., 2024).

8. Bar Chart on Willingness to Adopt AI for Sustainability: The result of willingness to adopt AI for sustainability reveals a spectrum of responses, but the majority of the respondents fell in moderate or high degree of willingness. This shows that though there might be some level of uncertainty concerning AI adoption, there is also an equal level of interest, which may mean that if the challenges that come with the integration are solved in the future, there will be a great chance of its adoption (Olawade et al., 2024).

Overall Insights:

The numbers and statistics indicate that there is a rather convoluted environment where AI is considered a useful solution for climate change prediction but is unable to be implemented due to several financial, technical, and policy barriers. Some respondents are quite confident about the efficacy of the AI, while others are not, and simple exposure to AI cannot be tied to high levels of confidence. To increase the level of integration, researchers may have to dedicate efforts to eliminating the mentioned barriers and improving the stability of the AI perception measurements in the following research (Talaat, Aljadani, Badawy, & Elhosseini, 2024).

Discussion



Online ISSN: 3007-309X Print ISSN: 3007-3081 https://jmhsr.com/index.php/jmhsr/issue/view/7



This quantitative analysis offers a good insight into the use of AI methods to integrate into the computation models that predict climate change. This research captures a multi-fold reality of the environmental science stakeholders' perception of AI, the technical specifications the technology requires to be effective, and the available opportunities for AI. The absence of normal distribution, as indicated by the Lilliefors test, and the low internal consistency, as discussed by Cronbach's alpha, imply the fact that people might hold attitudes towards AI in various ways and these ways might be due to several external factors. This diversity is important to capture the fact that respondents are in different familiarity and experience levels with AI differently (Rusilowati, Ngemba, Anugrah, Fitriani, & Astuti, 2024).

The lack of correlation between the degree of familiarity with AI and the confidence in AI's efficiency established by the coefficient of determination undercuts the idea that enhancing AI literacy would necessarily translate into confidence in AI's contribution to climate modeling. Rather, this means that confidence may be highly correlated with the practical use and effectiveness of AI in environmental initiatives. Deaux admits: 'It seems quite reasonable to assume that practitioners might require such exposure to practical AI applications that are demonstrably improving the accuracy of climate predictions before they develop high confidence in such systems (Rusilowati et al., 2024).'



Online ISSN: 3007-309X Print ISSN: 3007-3081 https://jmhsr.com/index.php/jmhsr/issue/view/7



The challenges that have been identified particularly the perceived lack of support from the government and high costs remind people about the problem of AI integration which is structural and systemic. These findings therefore point to the fact this the is is need for institutional and financial support to enhance the integration of AI in climate forecasting models. For AI-driven tools to be mainstream, both bare-bones policy support and funding have to create the necessary incentives for the changes needed in this field of climate science. However, the respondents' attitude toward the use of AI for sustainability, as illustrated in the bar chart, shows that there is a high level of understanding and enthusiasm among the professionals to consider AI when it comes to combating climate change (Biazar, Shehadeh, Ghorbani, Golmohammadi, & Saha, 2024).

This is a positive sign and it means that if the hurdles can be fixed then there is a great possibility of preparing for AI in climate models. Therefore, this research emphasizes the calls for a more focused approach in dealing with AI challenges in climate change predictions to ensure that AI practitioners can see the practical benefits of the technology. In addition, it is seen that improving the measurement instruments to obtain more accurate results concerning perceptions and experiences will also be essential in the following studies to reveal the factors that make AI integration in climate science multifaceted (Biazar et al., 2024).

Conclusion

The objectives of this research were: To identify the AI technologies involved in the use of climate change forecasting models to compare the quantity of perceptions, barriers, and opportunities. The study shows that despite a fair level of interest in AI adoption issues like high costs and lack of governmental support are major barriers to widespread use of AI. This lack of strong correlation might tell us that increasing familiarity with AI only has little effect on confidence in its efficacy; consequently, application in use cases or shift in successful AI stories may be more persuasive.



Online ISSN: 3007-309X Print ISSN: 3007-3081 https://jmhsr.com/index.php/jmhsr/issue/view/7



Nevertheless, there is still energy in embracing Artificial intelligence for sustainability purposes. This implies that when resources and appropriate support are provided, there is a big probability that the aspect of climate change will benefit from the use of Artificial Intelligence in improving the models of forecasting. Yet, to obtain such integration, technical as well as systemic issues have to be taken into focus. There is a need for more funding and change in the policies to show more tangible use of AI in the field of environmental science.

In general, it is argued that AI's representation in climate models requires more extensive consideration by moving beyond the technological perspective and including structure and stakeholders. What is more, the outlined barriers can be overcome leading to the priming application of AI in fighting climate change and enhancing prediction accuracy.

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