Received: 18 March 2024 | Revised: 25 April 2024 | Accepted: 1 May 2024
DOI: 10.1002/sd.3037

RESEARCH ARTICLE

Sustainable Development WILEY

Forecasting sustainable development goals scores by 2030 using machine learning models

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Abstract

The Sustainable Development Goals (SDGs) set by the United Nations are a worldwide appeal to eliminate poverty, preserve the environment, address climate change, and guarantee that everyone experiences peace and prosperity by 2030. These 17 goals cover various global issues concerning health, education, inequality, environmental decline, and climate change. Several investigations have been carried out to track advancements toward these goals. However, there is limited research on forecasting SDG scores. This research aims to forecast SDG scores for global regions by 2030 using ARIMAX and LR (Linear Regression) smoothed by HW (Holt-Winters') multiplicative technique. To enhance model performance, we used predictors identified from the SDGs that are more likely to be influenced by Artificial Intelligence (AI) in the future. The forecast results for 2030 show that "OECD countries" (80) (with a 2.8% change) and "Eastern Europe and Central Asia" (74) (with a 2.37% change) are expected to achieve the highest SDG scores. "Latin America and the Caribbean" (73) (with a 4.17% change), "East and South Asia" (69) (with a 2.64% change), "Middle East and North Africa" (68) (with a 2.32% change), and "Sub-Saharan Africa" (56) (with a 7.2% change) will display lower levels of SDG achievement, respectively.

KEYWORDS
ARIMAX, artificial intelligence (AI), Holt-Winters' multiplicative, linear regression, sustainable development goals (SDGs)

1 | INTRODUCTION

The concept of sustainable development focuses on achieving intergenerational equity and optimizing consumption to fulfill the needs of future generations (Keeble, 1988). After the definition of sustainable development by the Brundtland Commission, it was emphasized that economic growth cannot guarantee sustainability because it will lead to the reduction of natural resources and the deterioration of environmental services (Hamilton & Clemens, 1999; Repetto et al., 1989). Sustainable development is achieved through a balance among the three dimensions of environmental, economic, and social sustainability and their interconnectedness (Brusseau, 2019). Due to the urgent need to address global challenges in various sectors, an international consensus was formed on the Sustainable Development Goals (SDGs) (Singh et al., 2023). In 2015, an agreement was approved by 193 members of the United Nations (Schmidt-Traub et al., 2017). It was decided to regularly review the progress of the goals at regional, national, and global levels (Nations, 2015). The SDGs are a set of 17 guiding goals, focusing on aspects of human development, poverty reduction, ensuring security, and protecting the planet (Mazzi &

Floridi, 2023; Weststrate et al., 2019). Moreover, they lay the groundwork for organized and synchronized efforts to create a sustainable future all around the world (Costanza et al., 2016). Since their adoption, these goals have played a key role in promoting research and the development of new technologies (Singh et al., 2023).

Before the SDGs' introduction on the global stage, there was a strong inclination towards adopting smart technologies to address global issues (Sharifi et al., 2021). Today, it is argued that the smartification and use of Artificial Intelligence (AI)-based technologies have the potential to speed up the implementation of SDGs (Leal Filho et al., 2024) and can address most of the challenges faced by cities (Joia & Kuhl, 2019). In a broader context, AI has the potential to influence SDG 3 by leveraging sophisticated clinical decision support systems, computer vision technologies, image processing techniques, and electronic health records (Liengpunsakul, 2021; Singh et al., 2023). Furthermore, AI can play a role in impacting SDG 7 through the enhancement of smart grids, electric vehicles, and wireless sensor networks (Singh et al., 2023; Vinuesa, Azizpour, et al., 2020; Vinuesa, Theodorou, et al., 2020). Integrating AI into educational settings can contribute to SDG 4 by elevating the quality of education through applications like natural language processing and intelligent learning environments (Vinuesa, Azizpour, et al., 2020). Addressing concerns related to climate change and sustainable energy sources aligns with SDG 13, where AI can be instrumental (Singh et al., 2023).

However, it should be noted that while AI has high potential, its development involves potential trade-offs and difficulties related to privacy and cyber security, infrastructure upgrade costs, the digital divide and lack of skills, the risk of increasing the cost of living, the reproduction of social biases, and biased decision-making (Sharifi et al., 2024; Wang & Siau, 2019). However, the UN can ensure the successful attainment of the SDGs by implementing regulatory standards and international guidelines for artificial intelligence to mitigate any potential adverse impacts on the SDG (Truby, 2020).

Although many attempts and efforts are being undertaken globally to accomplish the SDGs, the pace of advancement is not keeping up with expectations. Therefore, major concern is whether the SDGs will be achieved on an international scale by 2030 (Asadikia et al., 2021). For this reason, in particular, regular tracking and evaluation of the success of achieving the SDGs at several levels—regional, national, and sub-national—over time can assist nations in identifying critical concerns regarding their own SDG advancements and the differences in those advancements among countries (Huan et al., 2021; Xu et al., 2020). Forecasting SDG scores of different regions not only facilitates an international comparison but can also help to "identify priority areas for action" (Biggeri et al., 2019) and "formulate targeted policy action" (Huan et al., 2021). In this regard, the SDGs indicators are a comprehensive measures of countries' progress (Biggeri et al., 2019; Sachs et al., 2018). The current study aims to forecast global SDG scores by 2030 using machine learning models. By reviewing previous studies, we identify the SDGs that are more likely to be affected by AI to serve as models' predictors.

Studies conducted in different countries show that monitoring and predicting the achievement of the SDGs is one of the main research focuses. In Portugal's case, Firoiu et al. (2022) used the ARIMA method to predict the achievement of SDGs until 2030, showing that favorable scores (above average) are predicted for 69 indicators. The highest are in "SDG 4" and "SDG 5", and the lowest achievements are in "SDG 2" and "SDG 9". In the case of Italy, Dello Strologo et al. (2021), using the FORECAST.ETS function and the dynamic index method predicted that this country will approach the EU average in "SDG2", "SDG9" and "SDG3" indicators by 2030, and it is necessary to adopt effective strategies to improve "SDG8", "SDG10", and "SDG11" indicators. The statistics provided by Eurostat became the basis of some research in predicting the SDGs; for example, Boto-Álvarez and García-Fernández (2020) showed that, in its commitment to the 2030 agenda, Spain must adopt special measures and public policies in the fields of sustainable agriculture, education, gender equality, sustainable energy, and poverty eradication.

Firoiu et al. (2019) showed Romania's progress in achieving SDGs is below average using dynamic analysis methods and the FORECAST. ETS function. Romania will reach the European Union average in targets including "SDG 7, 11, 13, 14, and 17" by the year 2030. However, it faces challenges in achieving other targets. It is recommended to increase stakeholders' participation and develop targeted strategies to enhance the achievement of the SDGs in this country. This can be achieved through close cooperation between government representatives at the local, national, and international levels. SDG forecasting on a global scale was done in only one study to predict the progress of SDG4 until 2030 (Friedman et al., 2020). The results showed that in 2018, the gender gap in education, except for "North Africa", "Sub-Saharan Africa", and "Middle East", had disappeared. Also, between 2017 and 2030, educational inequality will continue to decrease globally, so that women in 18 countries are expected to have a higher level of education than men by 2030. However, significant disparities are still projected to exist in the mentioned regions.

Some studies have specifically identified the influence of AI on SDG targets. An example focusing on "China" examines the role of AI in achieving the SDGs (Liengpunsakul, 2021). The most important technologies for achieving the SDGs are identified in "SDG3", "SDG7", and "SDG9." Further, this research argues that the government's readiness to accept AI has a strong positive relationship with the economic ("SDG 7, 8, 9") and social ("SDG 1, 2, 3, 4, 5, 10, 11, and 16") status of societies. In this regard, Singh et al. (2023) has identified that the main areas utilizing AI to achieve the SDGs are "SDG 3, 4, 7, 11, 13, and 16." This insight is based on comprehensive bibliometric trends, path analysis, and content analysis of publications over the past 20 years. Vinuesa, Azizpour, et al. (2020) examined the power of AI in achieving the SDGs. The authors used a "consensus-based expert extraction process" in their study. The authors also argued that AI has a significant beneficial influence on the environment (93%), society (82%), and the economy (70%), aligning with the goals of "SDG14, SDG1, SDG4, SDG6, SDG7, and SDG9." They also argued that creating a gap in transparency, safety, and ethical standards and creating an unequal future are AI's most important negative effects on the SDGs. However, Sætra (2021) criticizes Vinuesa, Azizpour, et al. (2020), Vinuesa, Theodorou, et al. (2020) and considers their research to be very quantitative and experimental in nature. He states that the positive potential of AI on the SDGs has been exaggerated. The potential negative effects of AI in this context have been underestimated. He further points to the promotion of polarization, fake news, and the intensification of inequality within and between countries as the most important potential negative consequences AI creates for the SDGs.

Utilizing green technologies and green taxes can serve as an effective mechanism for attaining SDGs. A study by Aydin and Bozatli (2023) using the ARDL and NARDL panel methods shows that environmental taxes and green innovation encourage the consumption of renewable energy in 10 OECD countries. Similar findings by Kafeel et al. (2024) with the GMM method indicate the significant impact of renewable energy and green innovation on carbon emission control. Xie and Jamaani (2022), using the moment quantile regression method (MMQR), prove that green taxes and renewable energy significantly reduce carbon emissions in the G-7. In China, Zhang et al. (2023) confirmed the effect of increasing the green tax on reducing carbon emissions intensity and promoting environmental innovations using the new quantile autoregression method (QARDL). Mpofu (2022) argues that while the green tax in Africa can mitigate climate change issues and boost innovation, it also raises concerns about competitiveness and energy poverty, potentially threatening clean energy access (SDG 7) and poverty reduction (SDG 1).

In examining the relationship between environmental technologies and carbon emissions, Erdoğan et al. (2020) showed that the use of green technologies causes carbon emissions. Costantini et al. (2017), investigated the importance of environmental innovations in European industry and their effect on carbon emission control, predicting that these technologies would help improve environmental standards. Similarly, Zhang (2023) showed in ten populous Asian countries that innovations reduce carbon emissions and increase environmental sustainability when combined with technological advances. Naz and Aslam (2023), studying the cyclical impact of technology in the environmental sector in South Asia, found that environmental innovations effectively reduce carbon emissions. On the other hand, governance's role as a moderator of carbon emissions is only effective with environmental innovation.

In recent years, the use of machine learning models to predict economic and financial trends has attracted a lot of attention. In this context, forecasting the price of goods is important for market evaluation and decision-making by policymakers. Machine learning in predicting the selling price of corn with Gaussian regression methods (Jin & Xiaojie, 2024a), univariate neural network (NN) modeling (Xu & Zhang, 2021a), and steel products with Gaussian process regression (Xu & Zhang, 2023) has provided useful results to policymakers and market participants. In the energy sector, forecasting the prices of various commodities (crude oil, heating oil, and natural gas) using nonlinear auto regression neural network models (Jin & Xiaojie, 2024b) and hybrid ARIMA and metabolic nonlinear gray models (Wang, Li, Li, & Ma, 2018) has been an important effort for a wide range of energy market participants. In the context of demand forecasting, Wang, Li, and Li (2018), Wang, Li, Li, and Ma (2018), Wang, Song, and Li (2018) predicted the growth rate of energy consumption in China and India using single-linear, hybrid-linear, and non-linear methods in demand forecasting. Another study by Wang, Li, and Li (2018), Wang, Li, Li, and Ma (2018), Wang, Song, and Li (2018) found that the NMGM-ARIMA technique can improve the effectiveness of forecasting US shale oil production in the field of production forecasting.

Carbon emission modeling using combined MNGM-ARIMA and MNGM-BPNN models in the United States, India, and China improved forecasting accuracy compared to previous models, and the results showed that China and India will remain the main sources of carbon emissions (Wang et al., 2020). Forecasting with combined ARIMA-BP and BP-ARIMA models on the impact of COVID-19 on carbon emissions determined that the epidemic will further reduce carbon emissions in developing economies (Wang et al., 2022). Xu and Zhang (2021b) showed the usefulness of machine learning models in predicting housing prices in China. They developed a relatively simple neural network with different model settings over the data spitting ratio, algorithm, hidden neuron, and delay. This modeling greatly assists policy analysis in this field.

The literature review showed that some previous studies have forecasted the achievement of SDG targets at a national scale, and others had identified the challenges and potentials by examining the application of AI in SDGs. It appears that there is a gap on the topic of forecasting SDG scores at a global scale using predictors. The contribution of this research is to identify priority regions for taking effective actions in order to improve SDG scores. The results of this research can identify important concerns about the progress of the SDG score until 2030 and the differences between the regions of the world. This information helps policymakers and stakeholders (countries, organizations, and individuals) make informed decisions, develop strategies to improve SDG scores, and reduce disparities between world regions through the balanced allocation of resources.

The SDGs dataset is projected by the United Nations until 2030 and is planned to be updated, with potential revisions to the specific targets and indicators beyond 2030 (Sachs et al., 2023a). Therefore, this study aims to forecast the SDG scores by 2030 for global regions to ensure relevance and address changes in SDG scores within a relatively near-term horizon. This will be achieved by employing the ARIMAX andLR smoothed by HW multiplicative, incorporating predictors to enhance the model's performance. Several studies (Barzola-Monteses et al., 2019; Christen et al., 2020; Islam & Imteaz, 2020; Peiris & Singh, 1996) have mentioned using external predictors improves the model performance and accuracy; some studies (Chen et al., 2022; Zheng et al., 2021) specifically showed using the related predictors enhances the model accuracy. In this study, predictors were selected based on the combination related studies and filter selection technique from SDG targets. As the world is experiencing an AI revolution and many studies (Gupta et al., 2021; Liengpunsakul, 2021; Schoormann et al., 2023; Singh et al., 2022; Singh et al., 2023; Vinuesa, Azizpour, et al., 2020) claimed AI likely to influence on some SDGs in future, incorporating these goals into the prediction model might improve the performance and accuracy. Additionally, the filter

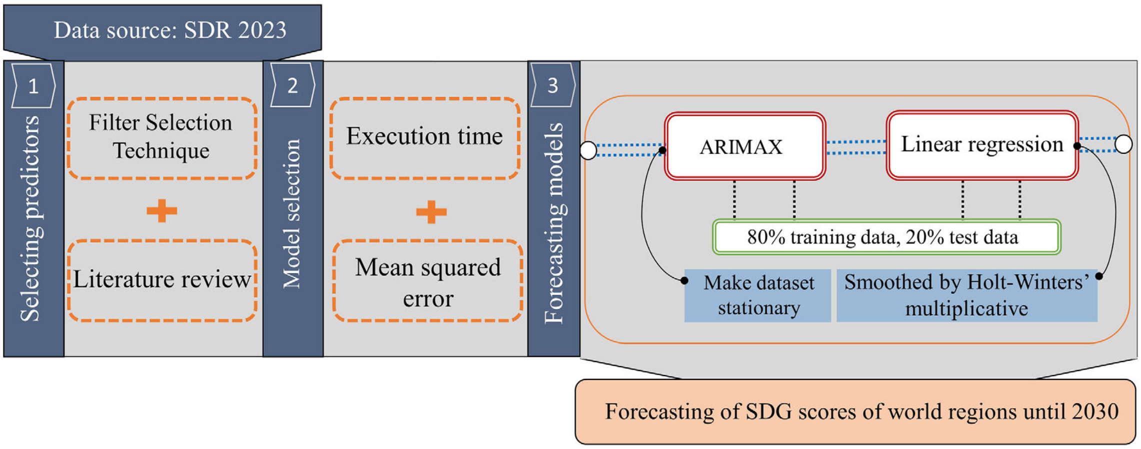

FIGURE 1 Methodological framework.

selection technique can be used to optimize the number of predictors by selecting the most suitable ones.

2 | MATERIALS AND METHODS

This study aims to build forecst models with predictors. To identify the predictors in this study, first we used previous studies to identify SDGs that are more likely to be influenced by AI in the future. The systematic literature search approaches were employed using keywords associated with SDGs, AI, and forecasting the SDG scores. The research team's backgrounds and previous knowledge and the literature guided their choice of keywords. The search strings are as follows: TOPIC 1 = (*"Sustainable development goals" OR "SDG" OR "SDGs") AND ("AI" OR "artificial intelligence") AND ("forecast" OR "predict"*), TOPIC 2 = (*"Sustainable development goals" OR "SDG" OR "SDGs") AND ("AI" OR "artificial intelligence"*), TOPIC 3 = (*"Sustainable development goals" OR "SDG" OR "SDGs") AND ("forecast" OR "predict"*) Topics include keywords, title, and abstract. Two sources, Scopus and Web of Science (WOS) were used to search for studies published between 1994 and 2023. After removing duplicates, the search across all databases returned 65 papers. After checking the titles and abstracts of these papers to ensure their alignment with the study objectives, 33 were selected for literature review.

Next, considering the number of predictors should be optimized (Peiris & Singh, 1996), we used the filter selection technique to identify the most appropriate targets to serve as our models' predictors. Finally, we use selected targets as predictors in our forecast models to improve performance and accuracy. The next step is to build forecast models using ARIMAX, and LR smoothed by HW multiplicative, with 80% of the data utilized for training and 20% for testing. LR was chosen due to its flexibility in adding predictors to the model and forecasting based on them (Uras et al., 2020). Additionally, a smoothing technique called Holt-Winters' multiplicative method was employed to enhance the LR model and enhance the accuracy of the forecasts (Hyndman & Athanasopoulos, 2018). The ARIMAX model is considered the most comprehensive class of time series forecasting models. It is particularly useful for addressing non-stationarity in datasets, as it can be transformed through differencing to achieve stationarity (Lai & Dzombak, 2020). All the analyses for this study were conducted using Python programming in the Google Colab code environment. The Statsmodels library was utilized for time series analysis and ARIMAX modeling, while the Scikit-Learn library was used for LR modeling. Additionally, Matplotlib was used for data visualization. Figure 1 summarizes the methodological framework for this research.

2.1 | Data source

The Sustainable Development Report (SDR) reviews progress made each year on the SDGs since their adoption by the 193 UN Member States in 2015. Dublin University Press, as an independent publisher, publishes progress reports in order to promote the achievement of the United Nations SDGs. The database of this research uses the latest version of this report that was published in 2023, which takes stock of progress made and discusses priorities to restore and accelerate SDG progress (Sachs et al., 2023b). The SDGs dataset includes SDG scores, 17 goals, and 169 targets across global regions from 2000 to 2022. The SDG dataset is characterized by a relatively small number of years (records) and a high number of SDG targets (features). The country groupings are based on geographic regions defined under the Standard Country or Area Codes for Statistical Use (known as M49) by the United Nations Statistics Division, which categorized countries as developed or developing and further divided them into sub-regions (Sachs et al., 2023a). The major regions in the SDGs dataset are categorized as follows: "Sub-Saharan Africa", "Northern Africa and Western Asia", "Central and Southern Asia", "Eastern and South-Eastern Asia", "Latin America and the Caribbean", "Europe, Northern America, Australia, and New Zealand "(the OECD countries). We chose to focus on regions rather than individual countries because the regional grouping dataset has fewer missing data points than individual countries.

TABLE 1 Statistical measurements of SDG scores.

Country	Mean	Standard deviation	Min	25% percentile	Median (50% percentile)	75% percentile	Max
East and South Asia	61.026	3.623	57.0	57.80	60.0	63.95	67.2
Eastern Europe and Central Asia	68.417	2.215	65.7	66.40	67.8	70.40	72.1
Latin America and the Caribbean	67.421	1.812	64.5	65.95	67.4	69.10	70.2
Middle East and North Africa	63.878	2.006	61.0	62.10	63.7	65.40	67.1
The OECD countries	75.052	1.779	72.2	73.65	75.0	76.55	77.8
Sub-Saharan Africa	49.221	2.723	45.2	46.90	49.2	51.75	53.1

Table 1 provides a comparison of the mean, standard deviation, minimum, 25th percentile, median, 75th percentile, and maximum values for six different country groups. Among these groups, OECD countries stand out with the highest mean SDG score of 75.052 and the lowest standard deviation of 1.779, indicating strong overall performance and relatively consistent progress in addressing sustainable development challenges. In contrast, Sub-Saharan Africa exhibits the lowest mean SDG score at 49.221 and the highest standard deviation at 2.723, suggesting comparatively lower average progress and greater variability in sustainable development performance across countries in this region. Eastern Europe and Central Asia have the mean highest SDG score at 68.417, followed closely by Latin America and the Caribbean at 67.421, Middle East and North Africa at 63.878, and East and South Asia at 61.026. In terms of standard deviation, East and South Asia have the highest variability at 3.623, followed by the Middle East and North Africa at 2.006, Eastern Europe and Central Asia at 2.215, and Latin America and the Caribbean at 1.812. The minimum, 25th percentile, median, 75th percentile, and maximum values also vary across these groups, reflecting different levels of performance and variability in addressing SDG scores within each region. The appendix (Table S1) provides statistical measurements for each predictor.

One of the primary challenges is the lack of comprehensive data for many SDG indicators, particularly in developing countries. Furthermore, the quality of available data is often questionable due to inconsistent methodologies, outdated sources, or incomplete coverage (Lyytimäki et al., 2020). Ensuring data quality is crucial for effective decision-making and policy formulation. Many countries, especially those with limited resources, face significant capacity constraints in terms of data collection, processing, and analysis (Warchold et al., 2022). The presence of missing values can lead to biased models, reduced accuracy, and ultimately, unreliable predictions (Emmanuel et al., 2021; Wang, Li, & Li, 2018). The SDG dataset includes both individual countries and regional groupings. To minimize the impact of missing data, the regional grouping data was chosen due to its lower prevalence of missing values (Mitra et al., 2023). This decision was crucial because machine learning models often struggle to perform optimally when faced with high levels of missing data (Hasan et al., 2021). By carefully selecting the predictors with no missing points and employing suitable forecasting models, the goal was to achieve higher accuracy and improved overall performance of the machine learning models (Shadbahr et al., 2023).

2.2 | Predictors selection

Techniques for selecting features can be divided into four categories: hybrid, wrapper, embedded, and filter selection. The filter selection technique is a suitable choice for modeling algorithm of this study because it selects features based on performance metrics (Brownlee, 2020). It is impractical to use all SDGs as predictors because using too many predictors can result in overfitting (Peiris & Singh, 1996). Additionally, targets are preferred over goals as predictors due to the similarity in range between the SDGs and the SDG score for each region. In previous section, we identified the SDGs that are likely to be influenced by AI in the future through a literature review. After eliminating targets with missing data, we utilized correlation-based feature selection (CFS) to rank individual targets that would improve the performance of the forecasting models (Jović et al., 2015). The final predictors include "n_sdg3_neonat," "n_sdg3_u5mort," "n_sdg3_tb," "n_sdg3_births," "n_sdg4_second," "n_sdg4_primary," "n_sdg7_cleanfuel," "n_sdg13_co2gcp." These predictors were selected from the targets of "Goals 3 (good health and well-being)", "4 (quality education)", "7 (affordable and clean energy)", and "13 (climate actions)".

2.3 | Model selection

When dealing with small time series datasets, the selection of an appropriate model is crucial for achieving accurate and efficient analysis. Therefore, the benchmark of machine learning models along with their corresponding execution times and mean squared errors was employed (Figure 2). This analysis was based on the target variable of 'SDG scores' and predictors for global regional groups. For models including 'MLP' (Multi-Layer Perceptron), 'GPR' (Gaussian Process Regression), 'SVR' (Support Vector Regressor), 'RFR' (Random Forest Regression), 'LR' (Linear Regression), and 'ARIMAX', the execution times are 5.63, 1.61, 0.46, 16.41, 0.27, and 0.35 s, while the mean squared errors are 210.25, 2695.85, 3.27, 0.12, 1.05, and 2.72, respectively. When comparing the machine learning models based on their performance on provided data, 'LR' and 'ARIMAX' outperform others in terms of both execution time and mean squared error. They have the lowest execution times of 0.27 and 0.35 and relatively low mean squared errors of 1.05 and 2.72, respectively. Additionally, 'RFR' has the highest execution time of 16.41 and 'GPR' has the

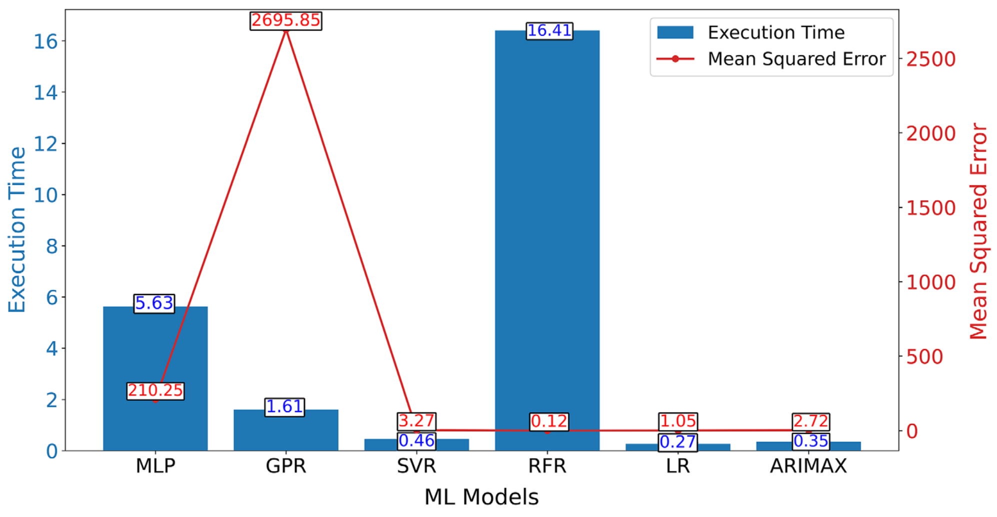

FIGURE 2 Benchmarking of machine learning models.

highest mean squared error of 2695.85. 'SVR' indicates efficient performance with a low execution time of 0.46, while its mean squared error is 3.27, which is higher than that of 'LR' and 'ARIMAX' but lower than 'GPR' and 'RFR'. Moreover, 'MLP' has an execution time of 5.63, which is higher than 'SVR' but lower than 'RFR'. The mean squared error of 210.25 in 'MLP' indicates a higher error rate compared to the other models. This comparison suggests that 'SVR' performs moderately well in terms of both execution time and mean squared error. Given the limited size of small time series data, simpler and more interpretable models such as 'ARIMAX' and 'LR' are the most efficient and accurate models due to their ability to balance accuracy and speed (Wang et al., 2022), while complex models like 'RFR', 'MLP', and 'GPR' may lead to overfitting and longer training times (Xu & Zhang, 2021a). By prioritizing models with a balance between accuracy, speed, and the characteristics of small time series datasets, researchers can ensure the selection of a model that best suits their analytical needs and facilitates valuable discoveries from the data (Xu & Zhang, 2023).

2.4 | Forecasting models

2.4.1 | ARIMAX model

The ARIMAX model is a time series forecasting method that incorporates exogenous variables. Autoregressive (AR), integrated (I), moving average (MA), integrated (I), and exogenous variables (X) are the constituent parts of this method (Siamba et al., 2023). The model comprises three essential parameters: p, d, and q. In this context, p represents the number of autoregressive terms, d represents the number of non-seasonal differences needed for stationarity, and q represents the number of lagged forecast errors in the prediction equation. The ARIMAX model is typically used for analyzing stationary time series data. Stationarity is achieved by differencing the series, which involves taking the difference between consecutive observations (Zhao et al., 2022). However, numerous real-world time series data exhibit non-stationary characteristics, signifying that their statistical properties change over time. This variability can pose challenges in accurately analyzing and modelling the data. To address this issue, differencing is employed as a technique to convert time series from non-stationary to stationary (Hyndman & Athanasopoulos, 2018).

The fundamental differencing formula is as follows:

$$y'_t = y_t - y_{t-1} \tag{1}$$

where y_t is the original time series at time t; y_{t-1} is the differenced time series at time t. This formula simply calculates the variation between the current value of the time order and the previous value. This removes the trend and seasonality from the data, making it more stationary (Hyndman & Athanasopoulos, 2018).

In terms of y, the general forecasting equation is:

$$y'_t = \mu + \phi_1 y'_{t-1} + \ldots + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q} + \beta_1 x_{1,t} + \ldots + \beta_k x_{k,t} \tag{2}$$

where μ is a constant, $\phi_1 y'_{t-1} + \ldots + \phi_p y'_{t-p}$ is the AR term with ϕ_1 to p as coefficients at p order, $-\theta_1 \varepsilon_{t-1} - \ldots - \theta_q \varepsilon_{t-q}$ is the MA term with θ_1 to θ_q as coefficients at q order, ε_t is a term of error for occasionally occurring random background noise at t, and y'_t is the differencing series; $x_{1,t} + \ldots + x_{k,t}$ are the predictor variables at time t; $\beta_1 + \ldots + \beta_k$ are the coefficients of the predictor variables (Lai & Dzombak, 2020; Pandit et al., 2023; Siamba et al., 2023).

2.4.2 | Linear regression model

The Linear regression model shows how a dependent variable and its independent factors relate to each other linearly. The primary target of this model is to determine the line that most suitably captures the data and effectively represents the relation between the variables that are independent and dependent (Uras et al., 2020). Subsequently, we constructed our LR model incorporating the selected predictors.

TABLE 2 The summary and accuracy of ARIMAX and LR smoothed by HW multiplicative models.

ARIMAX model						LR smoothed by HW multiplicative	
Groups	ADF test statistic	ADF test *p*-value	Model order (*p*, *q*)	AIC value	Mean square error	Margin error ME	SE
Latin America and the Caribbean	−2.710	.032	(5,0,2)	−2.40	0.013	0.297	0.151
East and South Asia	−1.848	.035	(1,0,1)	3.669	0.046	1.273	0.649
Eastern Europe and Central Asia	0.373	.048	(6,0,4)	4.648	0.041	0.769	0.392
Middle East and North Africa	−3.818	.002	(6,0,4)	0.050	0.015	0.470	0.239
The OECD countries	−4.245	.000	(7,0,7)	−1.01	0.003	0.132	0.067
Sub-Saharan Africa	1.774	.049	(1,0,6)	0.999	0.017	0.333	0.169

$$y_t = \beta'_0 + \beta'_1 x_{1,t} + \beta'_2 x_{2,t} + \ldots + \beta'_k x_{k,t} \tag{3}$$

Which includes the predicted coefficients but ignores the regression equation's error. Inserting the predictor variables' values $x_{1,t}\ldots,x_{k,t}$ for $t=1, \ldots, T$ returned the fitted values of y. Predicting future values of y is what matters to us in this situation, though (Uras et al., 2020).

Holt-Winters' multiplicative method

The Holt-Winters seasonal technique was applied to improve the model's accuracy, a method refined by Holt (1957) and Winters (1960) to effectively capture seasonal patterns in time series data. The Holt–Winters model requires elements such as level, trend, and season for accurate forecasting (Swapnarekha et al., 2021). The multiplicative strategy is preferred when the seasonal variations differ according to the series stage. The series is seasonally adjusted by splitting the seasonal elements, which adds up to about m in a given year. The seasonal element is displayed as a percent.

The component form for the multiplicative method is:

$$y_{t+h} = (l_t + hb_t) s_{t+h-m(k+1)} \tag{4}$$

Level Equation:

$$l_t = \alpha \frac{y_t}{s_{t-m}} + (1-\alpha)(l_{t-1} + b_{t-1}) \tag{5}$$

Trend Equation:

$$b_t = \beta^*(l_t - l_{t-1}) + (1-\beta)^*(b_{t-1}) \tag{6}$$

Seasonal Equation:

$$s_t = \gamma \frac{y_t}{l_t} + (1-\gamma) s_{t-s} \tag{7}$$

where y_t is the observed value at time t; l_t is the stage component at time t, b_t is the trend component at time t; s_t is the seasonal component at time t; α, β^*, and γ are the smoothing variables; h is the forecasting horizon; m is the number of seasons in a cycle; k is the integer part of (h/m) (Hyndman & Athanasopoulos, 2018).

3 | RESULTS

3.1 | ARIMAX model and LR smoothed by HW multiplicative method

The details and accuracy of ARIMAX and LR smoothed by HW multiplicative models are provided in Table 2, including the ADF test statistic, the ADF test *p*-value, the model order (*p*, *q*), the AIC value, and the mean square error for ARIMAX model and the margin error (ME) and standard error (SE) for LR model in six major world regions, including "Latin America and the Caribbean", "East and South Asia", "Eastern Europe and Central Asia", "Middle East and North Africa", "OECD countries", and "Sub-Saharan Africa". Each component in the table is essential for the LR and ARIMAX models. Figure 3 discusses autocorrelation and partial autocorrelation, allowing us to choose the best p and q for the ARIMAX model based on time lags (Zhao et al., 2022).

The Augmented Dickey-Fuller (ADF) test statistic and *p*-value are used to determine if the time series is stationary since stationary data is preferred in the ARIMAX model. Based on the ADF Test statistics provided for regions in Table 2, varying levels of stationarity in the time series data can be observed. "Latin America and the Caribbean" with a test statistic of −2.710, "East and South Asia" with −1.848, "Middle East and North Africa" with −3.818, "Eastern Europe and Central Asia" with 0.373, "OECD countries" with −4.245, and "Sub-Saharan Africa" with 1.774 exhibit different levels of stationarity in their respective data sets. These results show that these regions may have different trends or patterns in terms of stationarity. The statistical significance of the stationarity provided between the six regions is based on the *p*-values in Table 2. The "Middle East and North Africa" region has a *p*-value of .002, indicating a high level of statistical significance in rejecting the null hypothesis of non-stationarity.

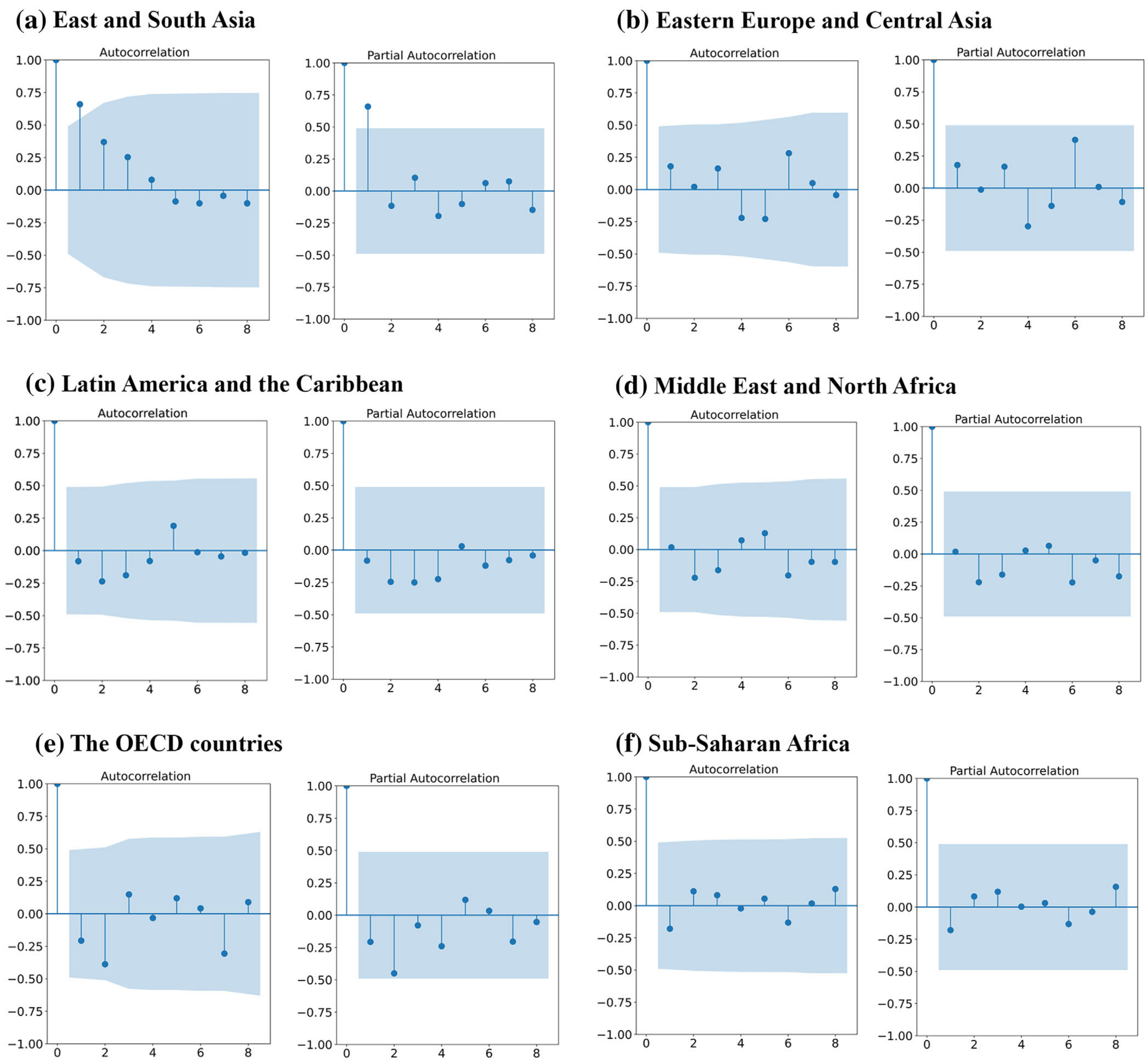

FIGURE 3 The ACF and PACF plots for major regions on a global scale.

Similarly, "OECD countries" showed a very low p-value of .000, suggesting strong evidence against the presence of non-stationarity in their data. On the other hand, "Latin America and the Caribbean", "East and South Asia", "Eastern Europe and Central Asia", and "Sub-Saharan Africa" have p-values of .032, .035, .048, and .049, respectively, implying different degrees of statistical significance in terms of stationarity.

The models' goodness of fit for each region can be compared using the AIC values in Table 2. "East and South Asia" and "Eastern Europe and Central Asia" have positive AIC values of 3.669 and 4.648, respectively, indicating that the models fitting their data may not be as good as those for other regions. Conversely, the "Middle East and North Africa", "OECD countries", and "Sub-Saharan Africa" have lower AIC values of 0.050, −1.015, and 0.999, respectively, suggesting better model fits for their data. The accuracy of the models in predicting the data can be compared for each region based on the Mean Square Error values in Table 2. "OECD countries" stand out with the lowest Mean Square Error of 0.003, indicating a higher accuracy in their model predictions. Following closely behind is "Latin America and the Caribbean" with a Mean Square Error of 0.013, suggesting relatively accurate model predictions for this region. In contrast, "East and South Asia", "Eastern Europe and Central Asia", "Middle East and North Africa", and "Sub-Saharan Africa" have higher Mean Square Error values of 0.046, 0.041, 0.015, and 0.017, respectively, indicating lower accuracy in their model predictions than the other regions.

TABLE 3 Values of SDG score using ARIMAX and LR smoothed by HW multiplicative time series models.

	Years	East and South Asia	Eastern Europe and Central Asia	Latin America and the Caribbean	Middle East and North Africa	The OECD countries	Sub-Saharan Africa
ARIMAX	2022	67.2	71.8	70.2	67.1	77.8	53.0
	2023	66.613	72.142	71.15	67.24	78.00	53.93
	2024	66.93	72.25	71.59	67.21	78.27	54.35
	2025	67.25	72.52	71.75	67.25	78.53	54.70
	2026	67.62	72.92	71.91	67.75	78.79	55.12
	2027	68.00	73.05	72.09	68.12	79.06	55.48
	2028	68.39	73.32	72.54	68.15	79.33	55.89
	2029	68.78	73.72	73.01	68.23	79.59	56.26
	2030	69.17	73.88	73.20	68.62	79.86	56.67
LR smoothed by HW multiplicative	2022	67.2	71.8	70.2	67.1	77.8	53.0
	2023	65.80	71.44	71.02	66.87	78.25	54.15
	2024	66.22	71.68	71.31	67.13	78.51	54.56
	2025	66.62	71.92	71.60	67.39	78.78	54.97
	2026	67.05	72.16	71.89	67.65	79.04	55.37
	2027	67.35	72.40	72.18	67.91	79.31	55.78
	2028	67.87	72.65	72.47	68.18	79.57	56.19
	2029	68.27	72.89	72.76	68.44	79.84	56.59
	2030	68.79	73.13	73.06	68.70	80.10	57.00

The margin of error (ME) is a statistical concept used to quantify the level of random sampling error present in the findings of a survey. A decreased margin of error signifies greater precision in the results, whereas an increased margin of error implies reduced confidence in the data. “OECD countries” stand out with the lowest margin error of 0.132, indicating a more minor deviation in their data. “Latin America and the Caribbean” closely followed, with a margin error of 0.297, suggesting a relatively lower error level in their data. In contrast, “East and South Asia”, “Eastern Europe and Central Asia”, “Middle East and North Africa”, and “Sub-Saharan Africa” have higher margin error values of 1.273, 0.769, 0.470, and 0.333, respectively, indicating a higher level of deviation in their data points compared to the other regions. The Standard Error (SE) values show the variability in the data for each region. “OECD countries” have the lowest Standard Error of 0.067, indicating a more minor variability in their data. “Latin America and the Caribbean” and “Sub-Saharan Africa” follow with SE values of 0.151 and 0.169, respectively, suggesting relatively lower variability. In contrast, “East and South Asia”, “Eastern Europe and Central Asia”, and “Middle East and North Africa” have higher SE values of 0.649, 0.392, and 0.239, respectively, indicating a higher level of variability compared to the other regions.

The autocorrelation and partial autocorrelation plots in “East and South Asia” (Figure 3a) displayed spikes at lag 1. In “Eastern Europe and Central Asia” (Figure 3b), the autocorrelation plot revealed the highest value at lag 6, whereas the partial autocorrelation plot displayed a peak at lag 4. The autocorrelation plot for “Latin America and Caribbean” (Figure 3c) revealed a significant spike at lag 5, and the Partial autocorrelation plot in this region revealed a strong autocorrelation at lag 2. Furthermore, in the “Middle East and North Africa” (Figure 3c), lag 6 was identified as a rise in the autocorrelation plot, while lag 4 was observed as a peak in the partial autocorrelation plot. “OECD countries” (Figure 3e) represented a peak of lag 7 in both the autocorrelation and partial autocorrelation plots. In addition, “Sub-Saharan Africa” (Figure 3f) showed lag 1 as a rise in the autocorrelation plot and lag 6 as a peak in the partial autocorrelation plot.

3.2 | Global forecasting using ARIMAX and LR smoothed by HW multiplicative from 2022 to 2030

The SDG scores for the six regions forecasted based on “ARIMAX” and “LR smoothed by HW multiplicative” (In short, LR) for 2022–2030 are shown in Table 3. In addition, Figure 4 represents the line graphs and displays historical training time series data, historical testing time-series data, and time-series forecasts using the ARIMAX and LR models. Graphs cover the years from 2000 to 2022, with the forecast extending to 2030. The ARIMAX model and LR model forecasts are shown with a 95% confidence interval for the predicted data. The forecasted SDG scores from the ARIMAX and LR models showed nearly identical values for all regions.

The range of changes in the SDG score in the “East and South Asia” region from 2000 to 2022 was between 57 and 67.2. ARIMAX forecasted a modest SDG increase for this region of countries at 69.17 in 2030. LR in the same period is expected to reach 68.790.

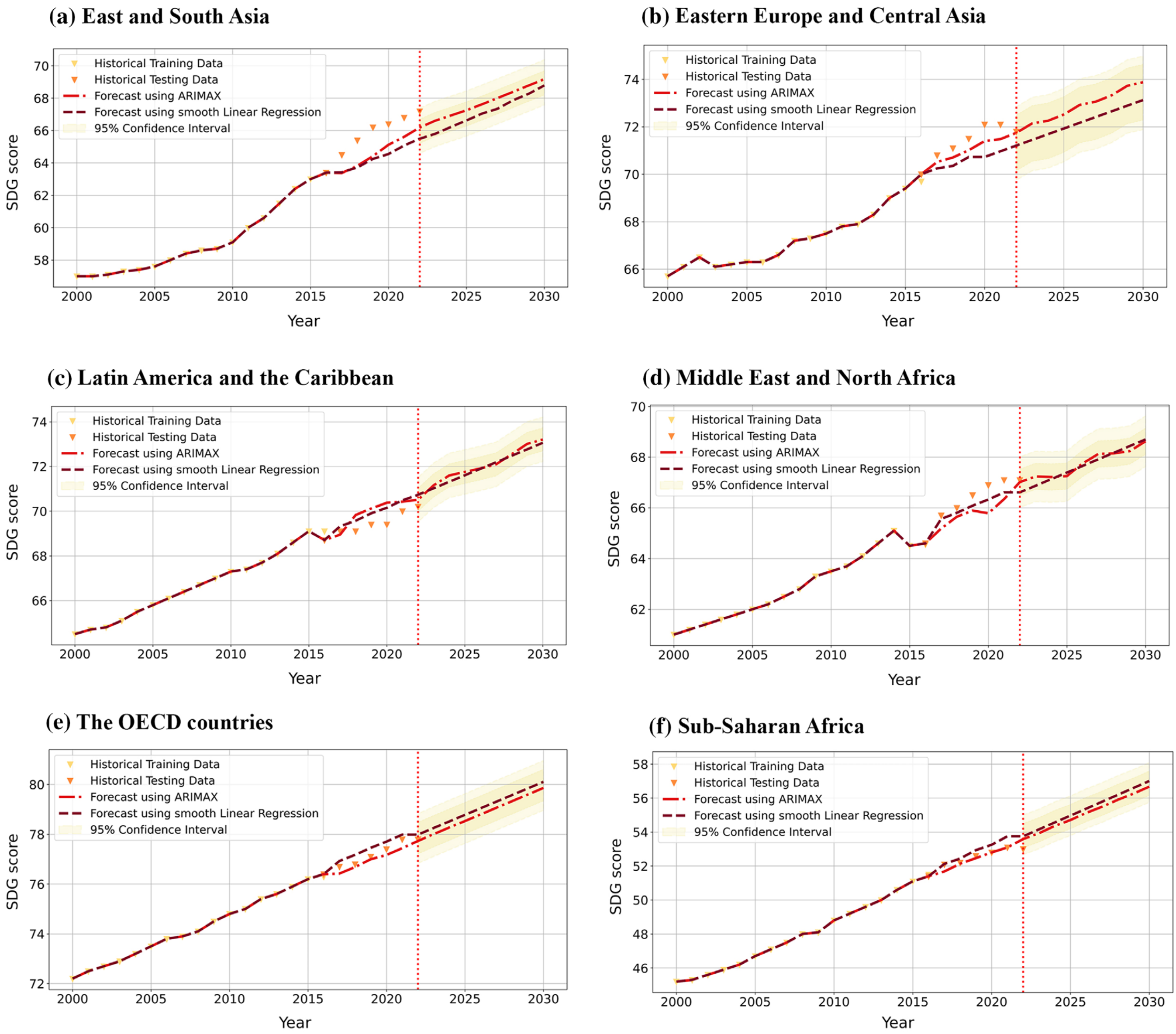

FIGURE 4 Forecasting SDG scores based on ARIMAX and LR smoothed by HW multiplicative time series models.

The range of changes from 2000 to 2030 in this region with the ARIMAX model will be 12.17, and with LR, it will be 11.79 (Figure 4a). Moving to the next region, SDG score of "Eastern Europe and Central Asia" increased slightly from 65.7 in 2000 to 71.8 in 2022. It will reach 73.882 and 71.2 in 2030 based on ARIMAX and LR forecasts, respectively. Overall, this region's range of changes from 2000 to 2030 will be 8.18 with the ARIMAX model and 5.509 with LR (Figure 4b). In "Latin America and the Caribbean", the SDG score variations between 2000 and 2022 ranged from 64.5 to 70.2. According to ARIMAX and LR, this region's SDG score will be 70.509 and 73.060 in 2030, respectively. Generally, the ARIMAX model expects a smaller range of change (6.009) in the SDG score from 2000 to 2030 compared to the changes expected by LR model (8.56) (Figure 4c). Between 2000 and 2022, "Middle East and North Africa" had changes in SDG scores ranging from 61.0 to 67.1. In this region, ARIMAX and LR indicated that the SDG scores will be 67.01 and 68.62 in 2023, respectively. Generally, the ARIMAX model forecasts changes in the SDGs range of 6.01 from 2000 to 2030, while LR forecasts changes of 7.629 during that same period (Figure 4d).

The SDG score for "OECD countries" showed a continuous upward trend, rising from 72.2 in 2000 to 77.8 in 2022. The ARIMAX and LR forecast results showed an increasing trend in 2030 at 79.861 and 80.107, respectively. In this region the range of SDGs changes from 2000 to 2030 with ARIMAX and LR forecasts will be 7.66 and 7.90, respectively (Figure 4e). The SDG score for "Sub-Saharan Africa" showed a gradual increase from 45.2 in 2000 to 53.0 in 2022. The ARIMAX and the LR forecast an increasing trend, with peaks of 56.670 and 57 in 2030. Overall, between 2000 and 2030 in this region, the ARIMAX and the LR forecast SDG score changes of 11.47 and 11.8, respectively (Figure 4f).

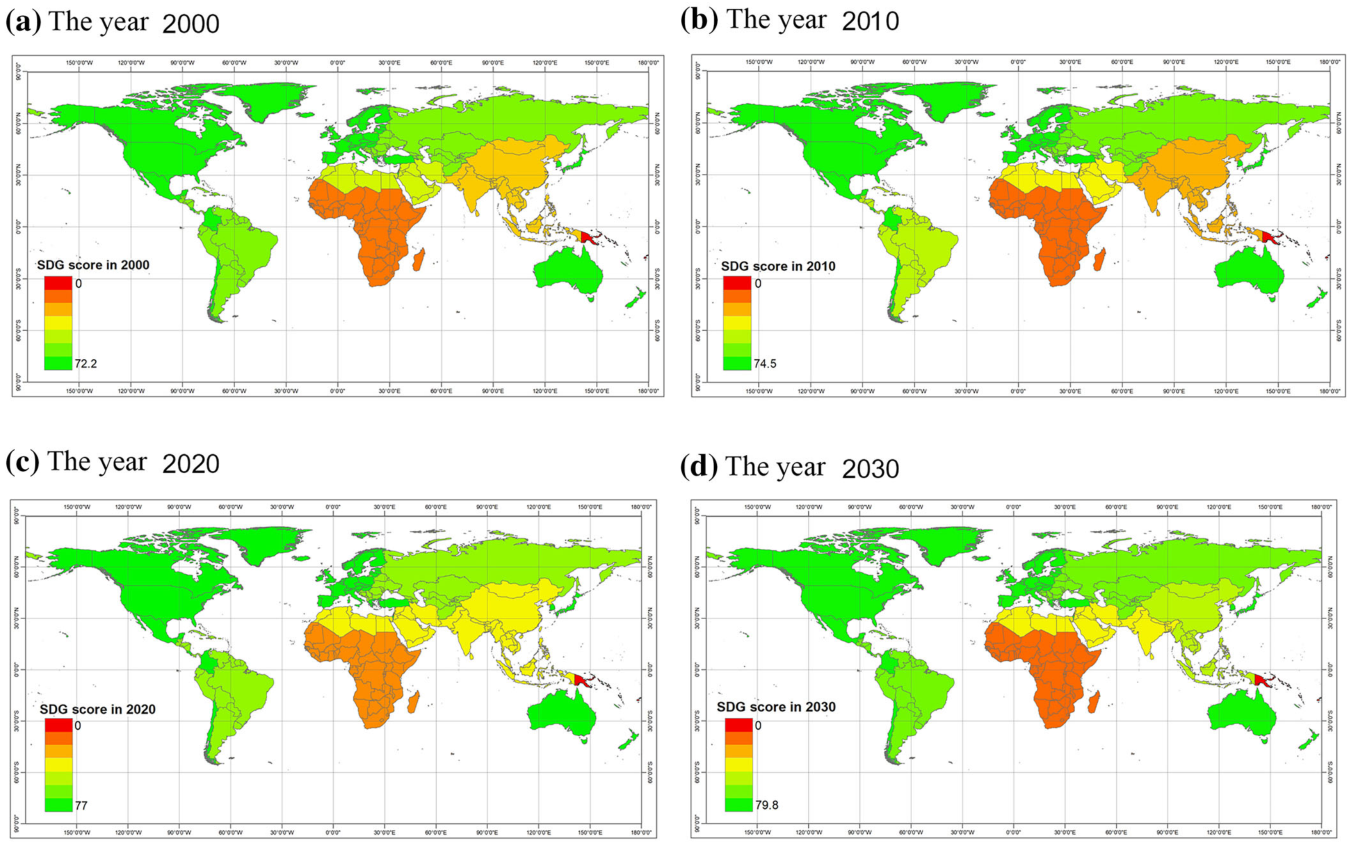

FIGURE 5 Forecasting SDG score based on ARIMAX and LR smoothed by HW multiplicative time series models.

The SDG scores from 2000 to 2030 for all regions are shown in Figure 5. It can be seen that the "OECD countries" consistently had the highest scores, starting at 72.2 in 2000 and increasing to 74.5 by 2010. "Latin America and the Caribbean" also showed a positive trend, with scores rising from 64.5 to 67.0 during the same period. "Eastern Europe and Central Asia" experienced a modest increase from 65.7 to 67.3. "Middle East and North Africa" and "East and South Asia" demonstrated smaller increases, with the former going from 61.0 to 63.3 and the latter from 57.0 to 58.7. "Sub-Saharan Africa", while showing improvement, still had the lowest scores, rising from 45.2 to 48.1. These results highlight varying levels of progress in achieving SDGs across major regions from 2000 to 2010 (Figure 5a,b).

A decade later, "Latin America and the Caribbean" showed an increase in scores from 67.0 in 2010 to 69.4 in 2020. "East and South Asia" also experienced growth, with scores rising from 58.7 in 2010 to 66.4 in 2020. "Eastern Europe and Central Asia" significantly improved, with scores increasing from 67.3 in 2010 to 72.1 in 2020. "Middle East and North Africa" also increased from 63.3 in 2010 to 66.9 in 2020. "OECD countries" had high scores, rising from 74.5 in 2010 to 77.4 in 2020. "Sub-Saharan Africa" showed progress as well, with scores increasing from 48.1 in 2010 to 52.8 in 2020. Overall, there is an increase in the scores for most regions over this decade (Figure 5b,c).

In the last decade of our analysis, "Latin America and the Caribbean" had an SDG score of 69.4 in 2020, which is projected to increase to a range of 73.060 to 73.209 by 2030 using ARIMAX and smooth Linear Regression models. The SDG score for "East and South Asia" in 2020 was 66.4, with a forecasted range of 68.790 to 69.179 in 2030 based on the two models. "Eastern Europe and Central Asia" scored 72.1 in 2020, which is expected to reach a range of 73.130 to 73.882 by 2030, depending on the forecasting methods. "Middle East and North Africa" started at 66.9 in 2020 and is projected to have scores ranging from 68.629 to 68.704 in 2030. "OECD countries" scored 77.4 in 2020, with forecasts ranging from 80.107 to 79.861 by 2030. "Sub-Saharan Africa" began at 52.8 in 2020 and is expected to reach a range of 57.004 to 56.670 by 2030, according to the ARIMAX and smooth Linear Regression models. Among the regions, "OECD countries" consistently exhibit the highest scores, with a score of 77.4 in 2020, increasing to 79.861 with ARIMAX and 80.107 with Linear Regression in 2030. On the other hand, "Sub-Saharan Africa" consistently shows lower scores compared to other regions, starting at 52.8 in 2020 and projected to reach 56.670 with ARIMAX and 57.004 with Linear Regression in 2030 (Figure 5c,d).

During the years 2022–2030, on average, "Sub-Saharan Africa" with 7.2%, followed by "Latin America and the Caribbean" with 4.17%, and "OECD countries" with 2.8%, have the highest growth rate in SDG score changes. In the following, "East and South Asia" with 2.64%, "Eastern Europe and Central Asia" with 2.37, and "Middle East and North Africa" with 2.32% have the lowest growth rate in the changes in SDG scores.

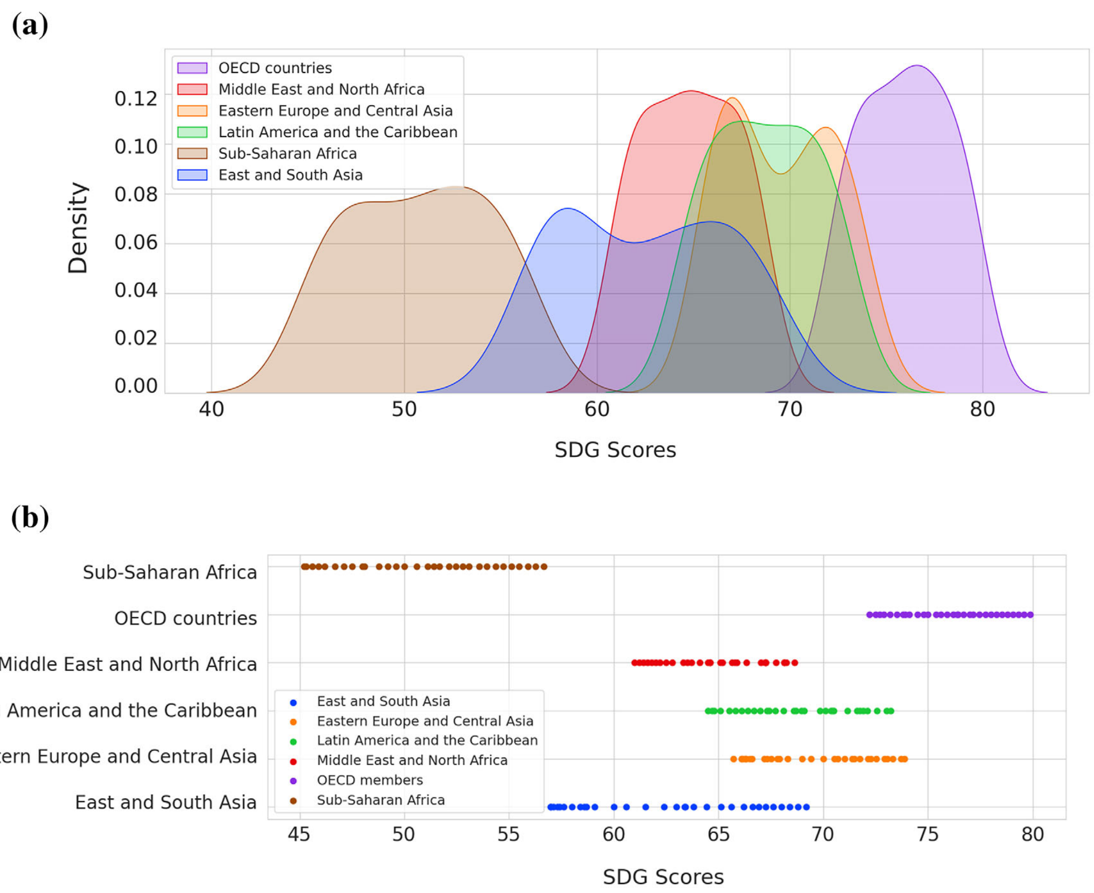

FIGURE 6 Density plot of SDG score changes from 2000 to 2030.

3.3 | SDG scores' distribution from 2000 to 2030

The density graph shows the distribution of SDG scores across different regions between 2000 and 2030 (Figure 6). When analyzing this plot, several factors should be considered, including the data distribution, skewness, and the placement of skew. Over the 30 years, the range of SDG scores in major regions varies from 45 to 80.

"Sub-Saharan African" has the highest variation in SDG scores from 45 to 57. The placement of the skew shows that this region has lower SDG scores compared to others. "East and South Asia" also show a big change in SDG scores ranging from 58 to 70. While the range of changes in data points for this region is similar to that of "Sub-Saharan Africa", the skewness indicates higher SDG scores in "East and South Asia" compared to "Sub-Saharan Africa". This region displays a lower peak compared to others. Meanwhile, "OECD countries" exhibit the most significant skew and peak among all regions. As the placement of skew shows, this region has achieved the highest SDG score. Furthermore, the concentration of data points is greater in this region compared to the others. The "Middle East and North Africa" region exhibited a high concentration of data points and displayed a prominent peak, with the skewness positioned between 62 and 68. "Eastern Europe and Central Asia", as well as "Latin America and the Caribbean", exhibit almost the same skew and distribution of SDG scores. The difference between these two regions is that "Latin America and the Caribbean" represented a single skew, while "Eastern Europe and Central Asia" had double skews. In general, the "OECD countries" have the highest level of SDG achievement, while the "sub-Saharan Africa" countries have the lowest level.

4 | DISCUSSION

Considering the various strategies and plans in global regions for accomplishing the SDGs, forecasting the SDG score will provide a clearer vision for the future. In this study, the two concepts of "Artificial Intelligence" and "Machine Learning" are distinct subjects. Machine learning is a specific technique within the broader field of AI, and it involves the development of algorithms that enable machines to learn from data and improve their performance on a specific task (Kühl et al., 2022). We used ARIMAX and smooth linear regression methods, which are subsets of machine learning methods, in order to predict the SDG scores of different regions of the world. Also, research predictors were selected from SDG indicators that are more likely to be influenced by AI in the future.

AI has facilitated the acquisition of new skills, popularized services, and enhanced production and repetition cycles. AI systems have contributed to reducing energy consumption (SDG 7) (Blasi et al., 2022; Liaqat et al., 2021), monitoring the environment (SDG

6, 13, 14, 15) (Ghadami et al., 2021; Parmentola et al., 2022), strengthening cybersecurity, enhancing global communication (SDG 16) (Khasawneh & Saleem., 2023), and improving health and treatment (SDG 3) (Hannan et al., 2020; Heras et al., 2020). AI is also expected to have a more significant and specific short- and long-term impact in areas such as the economy (SDG 8), society (SDG 11), and equality and inclusion (SDG 10) (Bolukbasi et al., 2016).

On the other hand, AI can cause "violation of privacy when exchanging health care" (Murdoch, 2021) and "increasing the divide in society due to unfair access to technology (Bulathwela et al., 2024)", which will limit the achievement of SDG 3 and SDG 7-SDG 4, respectively. Also, smart technologies and large computing centers are energy-intensive, which makes the expected result of AI's role in facilitating the achievement of SDG 12 and SDG 15 impossible (Sharifi et al., 2024). One of the most significant barriers to future AI development is the danger of replacing jobs with AI-based automation technology, or "technological unemployment" in general, which can have a direct negative effect on SDG 8 (Peters, 2019; Siau & Wang, 2018). The more advanced AI becomes, the more risks it will pose to humanity and society. This is to the extent that AI may make decisions that humans cannot control and comprehend (Dwivedi et al., 2021). Multiple studies show influence of AI on the SDGs as a double-edged sword (Goralski & Tan, 2020; Nasir et al., 2023; Schoormann et al., 2023), which if Failure to pay attention to the negative consequences of AI, sustainability problems in society, economy and environment will emerge.

Previous studies have identified the challenges and potentials by examining the application of AI in the SDGs (Goralski & Tan, 2020; Sharifi et al., 2024; Vinuesa & Sirmacek, 2021; Wamba et al., 2021; Wang & Siau, 2019). Several studies have focused on forecasting SDG scores on a national scale (Boto-Álvarez & García-Fernández, 2020; Herrero et al., 2021; Soltau, 2016). This study aims to forecast the SDG scores for global regions by 2030 using ARIMAX and LR smoothed by HW multiplicative. This study highlights strengths, especially in the utilization of machine learning prediction methods for SDG scores on a global scale. Additionally, predictors that are more likely to be influenced by AI in the future were integrated into ARIMAX and smooth LR to enhance the model's performance. The selection of predictors was informed by previous related studies and further refined through filter selection techniques to minimize the risk of overfitting. Targets were prioritized over goals as predictors due to the similarity in range between the SDGs and the SDG score for each region. The predictors were specifically chosen from the targets of SDG 3 ("good health and well-being"), SDG 4 ("quality education"), SDG 7 ("affordable and clean energy"), and SDG 13 ("climate action").

The extent of changes in forecasted years (2022–2030) for each region is as follows: "Sub-Saharan Africa" will change by an average 7.2% (about 4 units) from 53 in 2022 to 56.67 (ARIMAX) and 57 (LR smoothed by HW multiplicative) in 2030. In 2030, "Latin America and the Caribbean" will change by an average 4.17% (about 3 units), from 70.2 in 2022 to 73.209 (ARIMAX) and 73.060 (LR smoothed by HW multiplicative). An average 2.37% (about 1.7 units) of increase will be seen in "Eastern Europe and Central Asia" between 2022 and 2030, from 71.8 to 73.8 (ARIMAX) and 73.13 (LR smoothed by HW multiplicative). Based on the forecast results for "OECD countries," the change from 77.8 in 2022 to 79.86 (ARIMAX) and 80.1 (LR smoothed by HW multiplicative) in 2030 will be an average 2.8% (about 2 units). In 2030, "East and South Asia" will change by an average 2.6% (about 1.9 units), from 67.2 in 2022 to 69.17 (ARIMAX) and 68.79 (LR smoothed by HW multiplicative). Finally, there will be an average 2.32% (about 1.5 units) shift in the "Middle East and North Africa" region in 2030, from 67.1 (ARIMAX) to 68.62 (LR smoothed by HW multiplicative). According to the SDG scores, "OECD countries," "Eastern Europe and Central Asia," and "Latin America and the Caribbean" are rated first through third, respectively; "East and South Asia," "Middle East and North Africa," and "Sub-Saharan Africa" are ranked fourth through sixth in achieving SDGs in the world.

The difference in the SDG scores of different regions of the world in 2030 raises various issues, such as the state of economic development of the regions, social infrastructure, governance and political stability, environmental challenges, and demographic and cultural factors. In this regard, Çağlar and Gürler (2022), in their research, confirm the direct relationship between socio-economic and political-cultural status and sustainable development.

- It seems that the high difference in SDG scores in OECD countries compared to other regions is due to a developed economy, a high standard of living, suitable infrastructure, and strong governance.
- Eastern Europe and Central Asia, with a slight difference from Latin America and the Caribbean, rank second in the SDG score. This region has experienced significant socio-economic changes since the fall of the Soviet Union. Due to economic reforms and institutional political changes (rule of law and establishment of democratic institutions), some countries in this region have made good progress in the path of integration in the global market (Mokosch et al., 2015). The potential to accept changes in this region can be the main reason for the high SDG score compared to other regions of the world.
- Since 1960, the environmental conditions in Latin America and the Caribbean Sea have declined. The drivers affecting environmental changes in this region include population growth, weak governance systems, and inequalities in urban and rural areas. Pichs-Madruga (2020) forecasts that the imbalance in socio-economic development and its mutual consequences will intensify environmental problems. At the same time, Small Island Developing States (SIDS) have significant potential for eco-friendly economic growth (Coke, 2023). In general, LAC has the potential to achieve a high SDG score. These potentials include biodiversity and natural resources, renewable energy use, economic development innovation, and cultural diversity.
- East and South Asia, with a slight difference from the Middle East and North Africa, has the fourth place in the SDG score among world regions. Socially, this region's high population has created the main challenge in terms of poverty, health care, and education. The region of South Asia is home to about a quarter of the world's

population and is highly vulnerable to climate change (Schipper et al., 2008).

The rapid movement towards industrialization and the challenges of access to sewage and clean water can be one of the most important reasons why this region gets a relatively low score in the SDG. For the East and South Asian region, it is necessary to address its demographic and environmental challenges and benefit from its vast potential in the renewable energy sector (Pandey & Asif, 2022).

- The Middle East and North Africa region is among the weakest regions in achieving the SDG score (5th rank). It seems that instability and political conflicts in this region hinder the progress of SDG in the fields of peace, justice, and strong institutions (Kim & Sandler, 2020). Despite the region's economic diversity and oil-rich economy, about 23% of the population has an income of less than \$2 per day (Taweel et al., 2015). This can impede the attainment of SDG, particularly those related to economic growth and decent work. Many countries in this region have oil-rich economies, which will hinder efforts to reduce greenhouse gas emissions.
- The Sub-Saharan Africa region consistently lags behind other regions of the world in attaining sustainable development goals., mainly due to extreme poverty, challenges related to food security and health care, and the lowest SDG score. Inadequate infrastructure, especially in the energy and transportation sectors, has created extensive challenges to moving towards SDG. About 600 million people in sub-Saharan Africa do not have access to electricity, which is a limiting factor for improving socio-economic status (Tomala et al., 2021). Because the economy in this region is highly dependent on the environment and natural resources, there is the greatest vulnerability to environmental destruction (Zerbo, 2015). Gender inequality in access to education and economic opportunities (Friedman et al., 2020), poor human development index (HDI), and weak governance structures (Ukwandu & Jarbandhan, 2016) limit the achievement of higher SDG scores in this region.

Since the predictors were selected based on the most effective targets influenced by AI, it can be said that countries that are forecasted to perform better in terms of the selected SDGs are those that have made more advances in the realm of AI. On the other hand, the wide range of changes in SDG scores in the global south (Figure 6) can raise the hypothesis that AI may help regions with weaker political, cultural, and socio-economic status perform better in the future. The results of our research support the argument that to achieve higher scores in the SDGs, freedom (Dartey-Baah, 2014), strong institutions (White et al., 2001), good governance (Dartey-Baah, 2014; Nwankwo & Richards, 2001; Sachs, 2012), and high readiness are required (Liengpunsakul, 2021).

Furthermore, future uncertainties could have a significant impact on our findings. We based our forecasting on six predictors that AI is most likely to affect in the future. Identifying other effective predictors in the future will increase the results' uncertainty. Also, if one or more of these predictors have a different influence on SDG scores in the future, the results will be accompanied by more uncertainty. Numerous external factors will influence the status of the SDG scores in the regions until 2030: policy changes, global economic fluctuations, the occurrence of natural disasters or pandemics, and the speed of artificial intelligence developments in economic, social, and environmental fields are all examples. However, the level of attention to ethics in the field of technology development could cause the regions' SDG scores to differ from the research forecasts. The interconnected nature of the SDGs affects the complexity of future forecasting. For example, the use of clean technologies (SDG 7) will have a positive effect on reducing greenhouse gases (SDG 13), but the consequences for the infrastructure and industry sectors (SDG 8 & SDG 9) may not be positive.

4.1 | Policy implications

The results of this research can help governments and international organizations allocate resources and prioritize policies and interventions more effectively. Based on this, the allocation of resources and appropriate policies to support the regions "Sub-Saharan Africa," "East and South Asia," and "Middle East and North Africa" seem necessary. Furthermore, forecasting SDG scores will enable policymakers to develop monitoring frameworks to evaluate policy changes and understand how they affect sustainable development status. Policymakers can increase global collaboration in homogeneous regions in terms of SDG performance. In other words, higher SDG scores in "OECD countries," "Eastern Europe and Central Asia," and "Latin America and the Caribbean" provide the basis for knowledge sharing and international cooperation by these regions to support other regions with lower SDG scores.

According to the results, it seems that political, cultural, and socio-economic factors have a significant effect on higher SDG scores. Therefore, policymakers should consider structural factors when designing and implementing sustainable development strategies. In regions with lower SDG scores, the application of development policies based on artificial intelligence and technology (policy innovation) can improve the status of SDG progress (in this regard, our results show that "Sub-Saharan Africa," with a 7.5% increase in SDG score between the years 2022–2030, has the greatest potential for AI effectiveness in improving SDG scores). After identifying the most effective actions for priority global regions, governments and institutions (in general, policymakers) can cluster countries with similar political, cultural, and socioeconomic structures in order to prioritize "SDG "policies and interventions.

5 | CONCLUSION

This study forecasts SDG scores using machine learning models for global regions until 2030. Predictors are used to enhance ARIMAX and LR smoothed by HW multiplicative models' performance. According to the results, all regions are expected to show an upward trend in

SDG scores until 2030. In the target year, "OECD countries," "Eastern Europe and Central Asia," and "Latin America and the Caribbean" will score SDG 80, 74, and 73. "East and South Asia," "Middle East and North Africa," and "Sub-Saharan Africa" will have SDG scores of 69, 69, and 57. Although the SDG scores of the following regions, "Middle East and North Africa," "East and South Asia," and "Sub-Saharan Africa," will rise over time, "OECD countries" and "Latin America and the Caribbean" will remain more successful in achieving the SDG score. Among the regions examined, "Sub-Saharan Africa" has continuously shown the lowest levels of achievement in the SDGs. It seems regions with stronger political, cultural, and socio-economic structures tend to achieve higher SDG scores. The limitation of this research is the inability to investigate the possible uncertainties which causes changes in SDG scores. Based on the results of this study, countries can identify effective policies to improve the future of the SDG in different regions of the world. Additionally, forecasting results may boost worldwide competition and encourage collaboration between countries with similar levels of SDGs.

Uncertainties, the unpredictability of future events, and global dynamics present challenges and limitations in accurately forecasting the SDG scores. In this study, the authors tried to use indicators as predictors that are likely to be more affected by AI in the future. On the other hand, peer-reviewed articles and books on the impact of artificial intelligence are still increasing, and future research may determine the impact of AI on other indicators. That The authors were unaware of the results until now, and this is one of the research's limitations.

Future research could forecast SDG scores by the target year, focusing on economic, social, and environmental predictors. Finally, identify the differences and similarities with the results of the current research. Another potential area for future research is how to allocate global resources, with a focus on achieving a better balance of resource distribution in deprived regions, such as Africa. Real-world data and future projections typically involve uncertainty and variability, which the model may not fully capture. This can lead to challenges in accurately representing the complex dynamics present in real-world scenarios, and it underscores the importance of potential uncertainty and the nature of data when applying the model to practical situations. Therefore, in addition to our method, which was forecasting with Python, future studies could predict the SDG scores in regional groups within complex dynamic models. For simpler forecasting, future studies can use specialized statistical software such as SAS, SPSS, or Microsoft Excel, which provide advanced tools for time series analysis and forecasting. A challenge presents itself when selecting a prediction model, as the small dataset size necessitates the use of simpler models to achieve better accuracy and performance. Based on the performance of the 'SVR' model in the SDG dataset, future studies can consider utilizing 'SVR' for predicting SDG scores. While more complex models could also be considered, they would require further optimization. Furthermore, future studies can explore modeling the prediction of SDG scores without predictors or adjust the predictors to compare the results. As our study forecasts SDG scores using predictors that AI is likely to influence, future studies could concentrate on predicting AI performance and comparing it with SDG score growth to identify any potential relationships or differences.To provide comprehensive and more in-depth insights for decision-makers, future studies can focus on the contribution of targets and indicators to the changes in the SDG score. Also, in future studies, researchers can investigate policy changes on SDG scores. This examination can help one better understand the effectiveness of various policy initiatives in promoting sustainable development. Relying on methods such as longitudinal studies (tracking changes in SDG scores before and after the implementation of policy interventions), comparative analysis (conducting comparative studies to compare the effectiveness of different policies in changing the SDG score) and scenario analysis (visualization with simulation models to predict the change in SDG scores resulting from the proposed policies).

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

You can find dataset and regional grouping in here. All the codes used in this study are available. For accessing the forecasting of the SDG scores using LR smoothed by HW multiplicative click here. You can access the code for forecasting the SDG scores using ARIMAX click here.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Chenary, K., Pirian Kalat, O., & Sharifi, A. (2024). Forecasting sustainable development goals scores by 2030 using machine learning models. *Sustainable Development*, 1–19. https://doi.org/10.1002/sd.3037