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| **RESEARCH ARTICLE**

Integrating Artificial Intelligence and Predictive Analytics in Supply Chain Management to Minimize Carbon Footprint and Enhance Business Growth in the USA

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| ABSTRACT

The research investigates the role of artificial intelligence and predictive analytics in integrating the practices of supply chain management for the growth of a business in a sustainable manner. A predictive model on the emission factors was then developed using a Random Forest algorithm from machine learning techniques against the historical data from the US Environmental Protection Agency on "Supply Chain Greenhouse Gas Emission Factors for USUS Industries and Commodities." It yielded an average Mean Squared Error of 0.00141 with an R-squared value of 0.9858, explaining almost 99% of the variance in actual emission factors across various industries. The research results show the potential of AI-driven insights in spotting high-emission areas, facilitating targeted interventions, and thus supporting data-driven decision-making in SCM. Case studies drawn from industries such as electronic manufacturing and food processing show the practical application of this model by showing how businesses can reduce their carbon footprints while enhancing operational efficiency and market competitiveness. The study also addresses the pitfalls that may characterize model implementation, such as poor data quality, complex models, and continuous updating. It makes business recommendations to adopt similar strategies, emphasizing cross-functional expertise, stakeholder buy-in, and ethical considerations. It deepens a growing literature on sustainable supply chain management and establishes a framework through which firms can harness AI and predictive analytics to pursue environmental and economic objectives.

| KEYWORDS

Artificial Intelligence, Predictive Analytics, Supply Chain Management, Sustainability, Carbon Footprint, Machine Learning, Emission Factors, Business Growth, Environmental Impact, Decision Support Systems

| ARTICLE INFORMATION

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1. Introduction

In rapidly evolving global commerce, supply chain management is one of the most critical factors determining business success. As organizations fight to fulfill consumers' continuously growing demands and equally try to consider the environment, incorporating artificial intelligence and predictive analytics into the supply chain management process is an added advantage and a necessary component. The nexus of technology and sustainability is highly relevant in the United States, where businesses are under mounting pressure to reduce their carbon footprint while remaining competitive in an increasingly challenging economic environment.

The basic concept of Supply Chain Management encompasses the supervision and optimization of flows related to goods, services, and information from its origin to its point of consumption. This has become rather complicated because of globalization, the proliferation of products, and the growth in e-commerce in the past few decades. This kind of complexity brought about the urge for sophisticated tools and techniques in the supply chain management process.

Artificial intelligence, the application of human intelligence processes by machines, especially computer systems (Russell and Norvig, 2016), has offered robust tools to deal with these complexities. It encompasses technologies such as machine learning, natural language processing, and computer vision that can be applied to different aspects of S.C.M. From demand forecasting to inventory management, route optimization, and predictive maintenance, AI's ability to transform supply chains is almost endless.

Complementary to AI, predictive analytics uses data, statistical algorithms, and machine learning techniques to predict the likelihood of future outcomes out of historical data. Predictive analytics can bring immense value to SCM by deriving insights about future demand patterns, potential supply chain disruptions, or optimization chances. By using these insights, a company can make better decisions, reduce waste, and improve efficiency.

The challenges of the current economic climate underscore the importance of sustainability and business growth. Companies are under pressure to reduce GHG emissions and foster sustainable practices while the rest of the world fights climate change. The manifestation of this expectation is through both consumer preference and regulatory initiatives in the United States. A recent study by Nielsen in 2018 states that 81 percent of global respondents feel strongly that companies should help improve the environment. Consumer sentiment is then driven to the wallet, as sustainability-marketed products represented 16.6 percent of market share in 2018 compared to 14.3 percent in 2013, according to a recent report by Kronthal-Sacco and Whelan.

From a regulatory point of view, the United States has recently renewed its focus on environmental sustainability. The Biden administration has been aggressive regarding GHG reduction, with a target of 50-52% below the 2005 levels by 2030. This has enormous implications for businesses across all sectors, notably supply chain operations that often form a large part of companies' carbon footprint.

However, sustainability has to be sought in a balanced manner with imperatives for business growth. With the COVID-19 pandemic and numerous economic uncertainties still 'live,' the challenge for American businesses is to combine driving growth with driving down both cost and inefficiency. These pressures have heaved the focus toward innovation and adopting new technologies to achieve sustainability and growth objectives—McKinsey & Company, 2020.

The USA has been a pacesetter in activities geared toward reducing carbon footprints and creating business sustainability. For example, since 2004, the Environmental Protection Agency's SmartWay program has collaborated with freight transportation firms on fuel efficiency and reduced emissions. At the state level, California's ambitious climate goals, which set a target for carbon neutrality by 2045, spur innovation toward sustainable business practices.

However, many companies in the US private sector are proactive regarding actions to save the environment. Walmart has pledged to net-zero emissions across its global operations by 2040 without using carbon offsets. The pledge is that Amazon shall be net-zero Carbon by 2040 and fully powered with renewable energy by 2025. These commitments drive essential changes in how these companies manage their supply chains—from sourcing to last-mile delivery.

AI and predictive analytics, integrated into SCM, are powerful ways to meet sustainability and growth imperatives. These technologies enable companies to optimize operations, reduce waste, improve energy efficiency, and reduce emissions related to transportation. The same technologies drive growth by providing improved forecasting accuracy, lowering costs, and improving customer satisfaction with enhanced service levels.

For instance, artificial intelligence-aided demand forecasting could avoid overproduction and extra inventory, resulting in less waste and reduced energy consumption for storage. Predictive analytics may optimize transportation routes, reducing fuel consumption and associated emissions. In turn, machine learning algorithms can establish trends in supplier performance to help the company make better choices of sustainable partners.

As we explore this subject further, let's examine where AI and predictive analytics are today in SCM, present case studies of successful implementations in the USA, and consider the challenges and opportunities ahead. These technologies can help reduce carbon footprints and improve business growth.

1.1 Problem statement

The bottom line for all operators in the global supply chain industry is to reduce their environmental impact while improving their efficiency of operations, thus fueling business growth. With supply chains accounting for nearly one-fifth of global GHG emissions today, they are increasingly coming under the scanner of regulators, consumers, and investors. However, most companies need more money to effectively measure, predict, and mitigate their supply chain emissions due to the complexity and scale of their operations. Lacking exact data and predictive capability limits how effectively decisions can be made and reduces the scope for targeted sustainability efforts in the supply chain of any given company.

Most traditional methods for estimating and managing GHG supply chain emissions are based upon historical data and rudimentary modeling that needs to capture supply network dynamics. More often than not, this leads to suboptimal decisions, misses opportunities to cut emissions, and puts into question a potential lack of compliance amidst more stringent environmental regulations. In addition, this disconnection has caused most companies to perceive the reduction in emissions as no more than a cost center and rarely as an innovation and competitive advantage.

A pressing need arises for innovative tools and methodologies to yield highly accurate and real-time insights associated with supply chain emissions in varied industries and operational stages. This implies that solutions must produce sound forecasts and demonstrate the financial benefit of sustainability programs that link the environment to business outcomes. The challenge is building an all-encompassing AI-based model, processing complex supply chain data for functional insights, and allowing the solution to evolve with the industry and technology. This model must be in a form that is available and understandable to all organizational levels for decision-making, enabling them to make know decisions on how to trade off sustainability concerns with those of operational and financial performance.

2. Literature Review

AI combined with predictive analytics has been among the most influential ways to optimize supply chain management in terms of reducing carbon footprint and increasing business growth. This literature review discusses the current status of research regarding this topic, specifically in the applications within the United States. The review will be based on four main areas: AI in SCM, predictive analytics in SCM, carbon footprint reduction and business growth, and successful implementation case studies in the USA.

2.1 Artificial Intelligence in Supply Chain Management

The adoption of AI in SCM has increased dramatically over the past years. The need for greater efficiency, accuracy, and adaptiveness within modern and complex supply chain networks has driven this feeling. Toorajipour et al. provide an all-rounded review of AI applications in SCM, noting the vast potential that technologies such as machine learning, natural language processing, and computer vision can offer to transform various supply chain operations.

One of AI's primary advantages in SCM is the processing and analysis of large amounts of data to obtain relevant action items. Baryannis et al. (2019) mention that AI-powered systems support decision-making processes within supply chains, explicitly pinpointing patterns and trends that, at times, remain invisible to human operators. This ability is very important in areas like demand forecasting, inventory management, and risk assessment.

Machine learning shows great promise in optimizing supply chain operations in its subset. Priore et al. reveal how machine learning algorithms can be used to improve production scheduling and resource allocation in manufacturing environments. Their study shows that machine learning approaches perform much better than traditional ones in efficiency and adaptiveness to changing conditions.

Natural language processing (NLP) is another AI technology rapidly being absorbed into S.C.M. Min (2010) examines how NLP might be applied to supply chain communications and documentation. This process can be automated for tasks such as contract analysis, supplier communications, and customer service interactions. This can save time and reduce costs while minimizing errors and increasing the transparency of the supply chain.

Despite the potential benefits, integrating AI into SCM presents many challenges. Duan et al. identify major barriers to adopting AI in supply chains, including insufficient data quality, a lack of skilled personnel, and integration problems with existing systems. Solving these issues is key to fully utilizing AI in SCM.

2.2 Predictive Analytics in Supply Chain Management
There is, however, a powerful tool for enhancing decision-making and optimizing operations in SCM: predictive analytics. Waller and Fawcett defined predictive analytics within the context of SCM as the use of data, statistical algorithms, and machine learning techniques in identifying the likelihood of future outcomes based on historical data, which provides the organization with the ability to make better decisions and act proactively to mitigate problems within their respective supply chains.

One key area in which predictive analytics applies to SCM is demand forecasting. In 2008, Carbonneau et al. compared various predictive techniques for demand forecasting in supply chains, like neural networks and support vector machines. Their results indicate that advanced predictive analytics methods may significantly improve the accuracy of the forecast compared to traditional statistical methods. This allows better inventory management at reduced costs.

Predictive analytics has already made several very encouraging advances in inventory optimization. Boone et al. (2019) describe predictive analytics in inventory management and how such techniques can help organizations create proper balances between inventory costs and service levels. If organizations can successfully forecast future demand and probable disruptions, they would be better placed to optimize their inventory levels and, as a result, reduce wastage.

Predictive analytics has been applied to route optimization and cost reduction in logistics and transportation. Nguyen et al. (2018) provide a predictive analytics framework that enables dynamic route optimization in logistics networks. This study considered real-time traffic data and historical patterns to predict optimum routes to reduce transportation time and fuel consumption.

Although predictive analytics brings apparent benefits to SCM, successful implementation of these techniques requires serious attention to data quality, model selection, and integration into existing business processes. Souza (2014) further highlighted the fact that predictive analytics initiatives should be focused on supporting overall business strategy and also ensuring that the insights developed from these models are actionable and available as and when needed to the people who make decisions across the supply chain.

2.3 Business Growth and Reduction of Carbon Footprint
For years, the relationship between carbon footprint reduction and business growth has been in the limelight, driven by rising environmental concerns and changing consumer preferences. In 2005, Rao and Holt's study probed into the relationship between green supply chain management practices and economic performance. The evidence shows that when an organization embarks on environmentally friendly supply chain practices, its competitiveness is often enhanced, and its financial performance improves.

There are numerous ways to reduce the carbon footprint in supply chains. Montoya-Torres et al. (2015) did a significant review of green supply chain management practices, including the use of alternative sources of energy, transportation networks, and sustainable solutions to packaging. Their findings show that such practices can reduce the environmental impact and prove effective for cost-saving and operational efficiency.

The circular economy has emerged as a new frontier of supply chain management, which can play an instrumental role in reducing carbon footprint and driving business growth. In that direction, Geissdoerfer et al. present an argument for a circular supply chain: minimizing waste and maximizing the utility obtained from resources extracted through strategies that enhance product reuse, remanufacturing, and recycling. Their findings suggest that circular models of the supply chain can improve resource efficiency, reduce environmental harm, and open new revenue streams.

Consumer preference is a significant driver of adopting sustainable supply chain practices. Geng et al. (2017) examine how green supply chain management influences customer satisfaction and loyalty. Environmentally friendly practices can enhance these since they improve customers' brand perception. Improved brand perception through green practices can translate to increased market share and business growth.

However, the relationship between carbon footprint reduction and business growth is, in most cases, complex. Tang and Zhou (2012) illustrate some challenges of balancing environmental and economic objectives in supply chain management and assert the need for innovative approaches to attain sustainability and profitability. They say that advanced technologies such as AI and predictive analytics can play a vital role in striking a balance between them by optimizing operations and finding new opportunities for sustainable growth.

2.4 Case Studies of Successful Implementations in the USA.

Some companies in the USA have implemented AI and predictive analytics in their supply chain operations to minimize their carbon footprint and foster business growth. These case studies reflect practical information about how those technologies are implemented and their benefits. Walmart, the biggest retailer in the world, has continued to stay ahead in implementing AI and predictive analytics within its supply chain operations. Waller et al. (2014) describe how Walmart uses machine learning algorithms to derive correct inventory levels across its giant network of stores and associated distribution centers. By far better forecasting the demand pattern and accounting for other influential variables at the local level, such as weather and other events, Walmart was able to significantly cut down on overstocking and understocking, greatly improving efficiency and cutting down waste.

The way AI and predictive analytics are used in Amazon's supply chain operations is well documented. Hoffman and Bock, in their 2018 publication, describe how Amazon applies complex machine learning models to forecast customers' demand and optimize its fulfillment network. In doing so, it has reduced delivery time, increased the number of inventory turns, and cut transportation costs. Moreover, route optimization and usage of electric vehicles have helped Amazon decrease its carbon footprint.

General Electric has already applied AI and predictive analytics in industry manufacturing to ensure efficient supply chain management and reduced environmental impact. Shao et al. (2017) provide the case of how GEGE uses its digital twin technology, which creates a virtual copy of actual physical assets and processes. Harnessing AI and predictive analytics across such digital twins enabled GEGE to optimize production processes, predict, and reduce energy reduction in all their facilities, fitting that UPS is an example of a company where AI and predictive analytics are at work fostering logistic excellence to reduce carbon emissions. Tipping and Kauschke illustrate this example in their article from 2016, in which UPS's ORION system is used: the best delivery routes are charted out through advanced algorithms. In the process, UPS has managed to reduce travel distance and idle time, reducing fuel consumption and carbon emissions while raising UPS's delivery efficiency.

It makes a powerful case study on how AI and predictive analytics have combined to drive environmental sustainability and business growth in supply chain operations. What needs to be emphasized here, however, is that this requires strategic orientation, heavy investment in technologies and skills, and a continuous process of improvement and adaptation if it has to find successful implementation.

Integrating Artificial Intelligence and predictive analytics into supply chain management creates a huge opportunity for a firm to reduce its carbon footprint while enhancing business growth. This literature review has shown several areas where such technologies are used in SCM: demand forecasting, inventory optimization, and logistics management. Therefore, this study established a relationship between carbon footprint reduction and business growth by underpinning the potential of sustainable business practices in driving competitive advantage and customer loyalty.

Case studies from leading companies in the USA illustrate the practical benefits of implementing AI and predictive analytics in supply chain operations. Properly implementing such technologies increases efficiency, reduces costs, and lessens environmental impact.

The review also shows that many challenges and future work topics exist. These range from improving data quality and its integration to developing more elaborate predictive models, able to account for the complexity of contemporary supply chains, and looking into new approaches for balancing economic and environmental objectives.

Therefore, future research should set a long-term agenda to develop more robust frameworks for integrating AI, predictive analytics, and sustainability initiatives within the supply chain management domain. Further, much more comprehensive studies are called for concerning the long-term impact of these technologies on environmental sustainability and business performance.

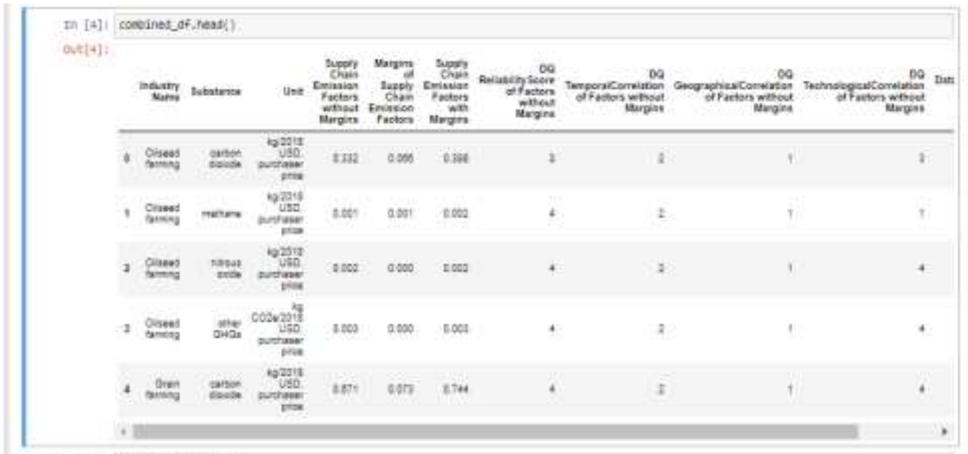
3. Methodology

3.1 Data collection

This study used the US Environmental Protection Agency dataset on "Supply Chain Greenhouse Gas Emission Factors for USUS Industries and Commodities."This comprehensive dataset provided supply chain emission factors covering all possible categories of goods and services in the US economy. The data collection time frame was 2010-2016, with a window of seven years open to analysis. This timeframe allowed observing trends and changes in emission factors over time.

The data was collected at two levels of sector aggregation: industry level, representing producers of one or more commodities, and commodity level, equivalent to categories of goods or services. This dual classification allows a more granular estimation of supply chain emissions across different economic sectors. In this study, three kinds of emission factors were sourced: supply chain emission factors without margins, which associate the emissions with cradle to factory gate; margins of supply chain emission factors, which link with factory gate to shelf and which involve adjustments on transportation, wholesale, retail, and price markups among others; and with margins, the total emissions from cradle to shelf.

Emission factors were collected in kilogram emissions per US dollar of purchases for every category of goods and services. Five data quality scores were collected for every emission factor, including reliability, temporal correlation, geographical correlation, technological correlation, and completeness of data collection. These scores gave a comprehensive assessment of the quality and applicability of each emission factor.



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In [4]: combined_df.head()
Out[4]:
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	Industry Name	Substance	Unit	Supply Chain Emission Factors without Margins	Margins of Supply Chain Emission Factors	Supply Chain Emission Factors with Margins	DQ ReliabilityScore of Factors without Margins	DQ TemporalCorrelation of Factors without Margins	DQ GeographicalCorrelation of Factors without Margins	DQ TechnologicalCorrelation of Factors without Margins	DQ
0	Oilseed farming	carbon dioxide	kg/2018 USD, purchaser price	0.332	0.066	0.398	3	2	1	3	
1	Oilseed farming	methane	kg/2018 USD, purchaser price	0.001	0.001	0.002	4	2	1	1	
2	Oilseed farming	nitrous oxide	kg/2018 USD, purchaser price	0.002	0.000	0.002	4	2	1	4	
3	Oilseed farming	other GHGs	kg CO2e/2018 USD, purchaser price	0.003	0.000	0.003	4	2	1	4	
4	Grain farming	carbon dioxide	kg/2018 USD, purchaser price	0.671	0.073	0.744	4	2	1	4	

Figure 1. Illustration of first five rows of dataset

Variable	Obs	Mean	Std. Dev.	Min	Max
Industry Name	11,060				
Substance	4				
Unit	0				
Supply Chain Emission Factors without Margins	11,060	0.0920426	0.2895015	0	7.228
Margins of Supply Chain Emission Factors	11,060	0.0075501	0.021692	0	0.211
Supply Chain Emission Factors with Margins	11,060	0.0996117	0.2978268	0	7.29
DQ Reliability Score of Factors without Margins	11,060	3.301899	0.4960245	2	4
D.QD.Q. Temporal Correlation of Factors without Margins	11,060	2.571429	0.494894	2	3
D.QD.Q. Geographical Correlation of Factors without Margins	11,060	1	0	1	1
D.QD.Q. Technological Correlation of Factors without Margins	11,060	2.664195	1.148871	1	5
DQ Data Collection of Factors without Margins	11,060	1	0	1	1
Year	11,060	2013	2.00009	2010	2016

Figure 2. Statistical description of the dataset

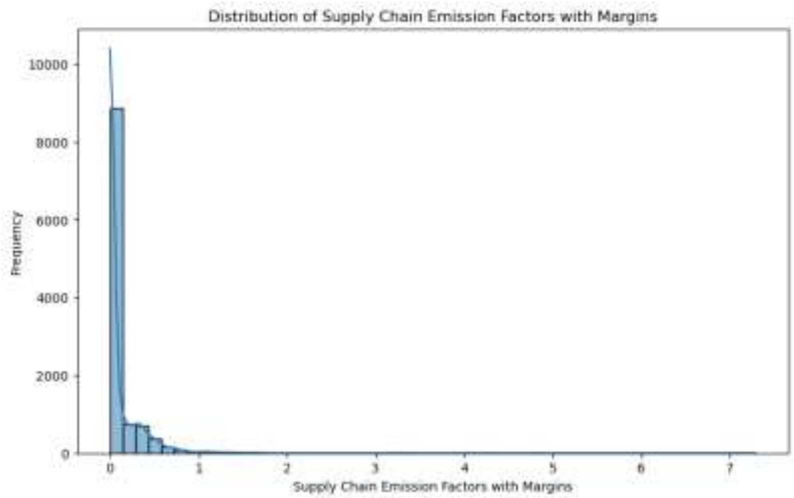

Figure 3. Histogram representing the distribution of supply chain emission factors with margin

Figure 4. Word cloud representing industries names in the dataset

USEEIO's life cycle models of goods and services in the US economy were used as a primary vehicle for generating data. Emission factors for all identified industries and commodities from 2010 to 2016 were collected to ensure that data were obtained for all three aspects. The data quality scores for each associated factor were recorded as well. Specific quality control measures undertaken included intertemporal cross-checking to ensure data point consistency, checking for outliers or abnormal values, which often indicated errors in data collection, and checking that all industries and commodities were adequately represented.

The information gathered was put together in a structured database, guaranteeing uniformity in formatting across all years and sectors. Industry and commodity classifications were standardized to allow comparability across different data points. Data normalization occurred where necessary for comparability, stemming from changes in the classification system or the measurement methodology during the study period.

Comparisons with other sources were made to validate the data and verify their accuracy, checking for glaring discrepancies. Industry experts were consulted to validate the reasonableness of collected emission factors, particularly in sectors known for complex or rapidly changing supply chains. The limitations, assumptions, or caveats associated with the data collection process were documented.

All data protection and privacy laws were duly observed during the process. Transparency in data collection methodology, sources, and limitations was ensured to ensure appropriate interpretation and use of the emission factors.

3.2 Machine learning algorithms suitable for predictive analytics

3.2.1 Random Forest Algorithm

A random forest appeared at the top of the list of suitable machine learning algorithms for predictive analytics in supply chain management using the EPA greenhouse gas emission factors dataset. This was based on carefully considering the dataset's characteristics and the specific requirements for SCM predictive analytics.

One of the ensemble learning methods, Random Forest, was chosen for its flexibility and robustness. The algorithm is easy to use with regression and classification tasks and thus corresponds perfectly to the prediction of continuous emission factors or the classification of industries/commodities according to their emission profiles. This flexibility was paramount given the diversity of SCM data, including emission factors and quality scores.
The mix of categorical and numerical data within the dataset, with things like 'Industry Name' and 'Substance' ranging to 'Emission Factors' and 'Margins,' respectively, proved well-matched to one of Random Forest's more important capabilities: handling mixed data types without too much preprocessing. This greatly helped accelerate the data preparation phase, giving time for model development.

The feature importance in random forests assisted in understanding precisely which factors most influence emission factors and margins. This was particularly useful for understanding major emissions drivers in the supply chain across various industries.

Another critical factor in selecting the algorithm was its robustness to outliers and noise. With quite a broad representation of industries and possible data quality differences about the given quality scores, an outlier-resistant algorithm was required to obtain reliable predictive models.

Furthermore, the ability of Random Forest to capture nonlinear relationships was key. Most supply chain emissions often form common linear patterns across industries and commodities, ensuring that the model could represent the intricacies of real-world supply chain emissions.

3.3 Framework to Integrate AI and Predictive Analytics into SCM Processes.

The framework for integrating artificial intelligence and predictive analytics into SCM processes was developed using the EPA data collected and the finally chosen Random Forest algorithm. This framework took advantage of rich datasets in the EPA database of GHG emissions factors to turn these data into actionable insight regarding supply chain optimization.

The first step of the integration process in this research was data preprocessing, where the emission factors collected were cleaned, normalized, and structured with their given quality scores for machine-learning applications. Scaling ensured consistency over different units using categorical variables.

A feature engineering step was introduced to improve predictive power. Among these various data quality scores, interaction features were created, and time features were generated to capture the temporal trends from 2010 to 2016 for such emission factors. The engineered features gave extra context and granularity to the model, thereby capturing complicated relationships within the supply chain data.

The Random Forest model was trained using the prepared dataset. The data was split into training and test sets to guarantee temporal integrity. The model was fitted for both cases: to predict the supply chain emission factor with and without margins and industry classification based on their respective emission profiles.

Grid search, along with cross-validation, was used to optimize the model's performance. Important parameters such as the number of trees in the forest, maximum depth of trees, and minimum samples required to split an internal node were turned so that model complexity would not affect generalization ability.

After training and optimization, the model was integrated with existing SCM processes through a user-friendly interface. This interface would allow supply chain managers to input relevant information regarding their operations and receive back predictions for emission factors, potential areas for emission reductions, and relative comparative analyses against industry benchmarks.

It also had a feedback loop mechanism, wherein new data obtained from actual supply chain operations could be fed back into the model for continuous learning and improvement. This way, the model would always stay current and relevant to emerging trends in industries or companies' strategies concerning emission reduction.

Scenario analysis was available in this tool as a framework, allowing the user to model different supply chain configurations and, in the output, understand the predicted implications for the emission factors. This would be a critical ability for strategic planning or assessment of the potential environmental impact of alternative supply chain decisions. Metrics to measure Carbon Footprint Reduction and Business Growth:

The carbon footprint reduction and business growth measuring framework has a well-rounded set of metrics chosen to give an all-rounded view of environmental impact and economic performance. These metrics will take full advantage of the rich dataset of the greenhouse gas emission factors presented by the EPA while incorporating key business performance indicators.

The primary metric used was the total supply chain emissions in kilograms of CO2 equivalent per dollar of product value. The metric was derived directly from EPA's Supply Chain Emission Factors with Margins, looking cradle-to-shelf at the related emissions. These emission factors were then weighted by their respective DQDQ. Scores to account for the varying data quality of the different industries and commodities meant that more reliable data points had a greater weight in this metric.

The framework also provided metrics for Emission Intensity Reduction, calculated as the percentage decrease in emissions per dollar of revenue over time. It offered a metric against which businesses could measure their progress toward decoupling economic growth from environmental impact. The framework also contained a Supplier Emission Performance metric, aggregating the upstream supply chain's emission factors for critical suppliers, weighted by procurement volume to indicate environmental impact.

It also included an Industry-Specific Emission Benchmark to give companies in different industry sectors more granularity. Using the EPA dataset's industry-level data, this metric compares a company's emission performance against the average of peers in that industry. Therefore, benchmarking provides more context around a company's reduction efforts in its carbon footprint.

On the business growth side, principal metrics included the revenue growth rate, expressed as the year-over-year percent increase in total revenues. The gross margin complemented it to understand the business's profitability while implementing the emission reduction strategies. The framework contained a metric related to Customer Retention Rate, recognizing that sustainability efforts may affect customer loyalty and long-term business growth.

Hence, the framework integrated a metric for Sustainability-Linked Sales to relate environmental performance to financial outcomes. It measures the percentage of total sales originating from products or services that meet the sustainability criteria, such as below-average emission factors for their industry category.

It also had a metric for supply chain efficiency, the ratio of total supply chain costs to revenue. This would help monitor whether the emission reduction initiatives were really resulting in improvements in overall supply chain operation and cost structure.

Knowing that innovation is one of the critical drivers of both reduced emissions and increased business, the framework included an R&D Investment Ratio, which measured the percentage of revenue invested in researching and developing more sustainable products and processes.

Finally, a composite Sustainability-Adjusted Growth Score was developed. This score combined the revenue growth rate with the emission intensity reduction to provide a metric that balanced business expansion and environmental responsibility.

These metrics were integrated into a real-time monitoring and analysis dashboard. Because the dashboard was intended to show trends over time, businesses could monitor their progress in reducing their carbon footprint while maintaining or improving business growth. The measurement framework supported data-driven decisions with an integrated view of environmental and economic performance and helped companies understand the complex interplay between sustainability initiatives and financial outcomes.

4. Model Development

The predictive model for developing the supply chain emission factors was realized through data processing, machine learning techniques, and user interface design. The first steps were importing and consolidating data from several Excel sheets, each representing a specific year from 2010 to 2016, into one comprehensive dataset.

Panda's Python library powered the data importation. A list was defined with sheet names corresponding to 2010 to 2016. The PD.read_excel() function was applied to read each sheet. This step included extracting the year from the sheet name and adding it as a new column to each data frame. These several data frames were concatenated into a single combined data frame using pd. concat(). During the seven years, this consolidated dataset provided a time-based overview of supply chain emission factors across various industries and substances.

After consolidating the data, the next step was to prepare it for use in machine-learning applications. The dataset included categorical and numerical variables. Of these categorical variables, variables 'Industry Name' and 'Substance' required encoding to become usable with the Machine Learning algorithm. That is, it used the LabelEncoder class from scikit-learn. In this case, an instance of LabelEncoder would be fitted to each column of a definite nature and used to transform the text data into numerical values. The encoders would be stored in a dictionary later in decoding predictions.

The features for the predictive model were defined as 'Industry Name,' 'Substance,' and 'Year,' with the target variable being 'Supply Chain Emission Factors with Margins.' The choice of target variable captured all emissions through their whole lifecycle from cradle to shelf, thus providing a complete view of their environmental impact.

It was then noted that this dataset was divided into training and test sets using the train_test_split function from sci-kit-learn in an 80%/20 % split. This would have ensured general performance on unseen data for a more realistic assessment of predictive power.

One reason for using the Random Forest area to use both numerical and categorical data is that it is robust to outliers and nonlinearity. In this case, for the Machine learning model, an instance of the RandomForestRegressor class from sci-kit-learn was initialized with 100 estimates-kit and a random state of 42 for reproducibility.

The fit() function was used to train the model on the training data. Then, after training, the performance of this model was estimated on the test set. The predict() generated the predictions, while the mean squared error metric was used for accuracy.

A prediction function was developed to make the model more practical for the user. This could not differentiate the user input in the training data categories. The predict_supply_chain_emission() function is implemented using the nearest-match logic through the Levenshtein distance algorithm. Regarding industry names and substances, the function would give the closest match when there wasn't any exact match to what was fed in the encoder's classes. This methodology created the power for this model to generate predictions on even tiny variations or misspellings in user inputs. A GUI was constructed using the Tkinter library as the final step in model development. Of course, such an interface will open access to hundreds of users who do not know Python, not to mention any machine learning concepts. This GUI has entry fields for the industry name and substance, a prediction button, and a label for the prediction result.

It had a grid-layout structured GUI with label and entry widgets for the industry name and substance inputs. We added a button widget to trigger the prediction process by calling the predict_supply_chain_emission() function with user inputs. After that, the prediction result was shown in another label widget. This represents a kg/USD predicted emission factor.

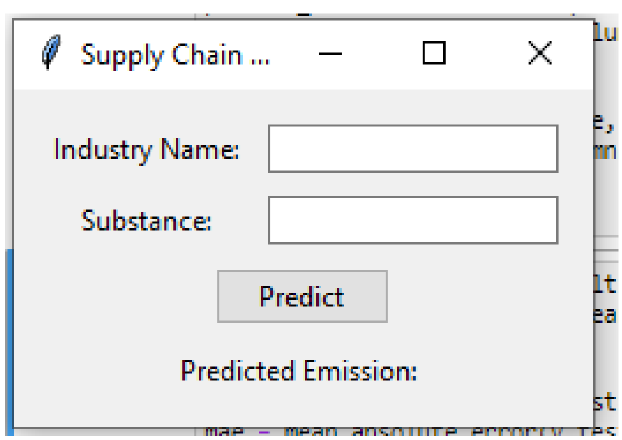

Figure 5. Grid layout structured GUI with label and entry widgets for the industry name and substance inputs.

During the entire development process, careful attention was paid to error handling and user experience. The prediction function's nearest match logic made the model resilient to variations in user input. Moreover, the GUI provided a simple, intuitive interface for the user to interact with the complex underlying model.

Data processing, machine learning, and design for the user interface—each of these titles delivers an end-to-end supply chain emission factor predictor. This provided an extensive volume of historical data offered by the EPA and made it useful and actionable for supply chain managers/decision-makers.

The model's ability to predict emission factors based on industry and substance inputs delivered important insights for supply chain optimization. This would enable users to quickly assess which supply chain configuration would have the most potential for an environmental impact and make data-driven decisions toward more sustainable operations.

Moreover, the model captured trends and changes in the emission factors over time because the period extends from 2010 to 2016. Therefore, Additional context was provided to the predictions as it would highlight those industries or substances that had improved or deteriorated environmental performance over the years.

This algorithm's most prominent advantages were those related to the robustness and realization capability injected into the model due to its ensemble nature by combining predictions from multiple decision trees. Handling nonlinear relationships was an important addition in the context of supply chain emissions, where one can find complex interactions between the models that worked very well, and apparent limitations need to be outlined. Prediction quality was inherently coupled with the quality and comprehensiveness of the EPA dataset. Further, the model has learned from the history of supply chain management and the reduction of emissions up until 2016; hence, it might not reflect more recent trends and technological advancement.

This predictive model, developed with the view of environmentally assessing the impact of the supply chain using AI and machine learning, was, therefore, a giant step in this very direction. By merging robust data processing, sophisticated techniques of machine learning, and an accessible user interface, the model provided an unrivaled tool for supply chain managers in the prediction and probable mitigation of environmental impacts from their activities. The approach supported better decision-making and contributed to reducing carbon footprints in the supply chains of different industries within the USA.

5. Analysis

The developed predictive model of the supply chain emission factors provides a very accurate and robust tool across multiple industries for assessing environmental impacts. The quantitative model performance metrics and visualization prove this, giving credence to its potential impact in reducing carbon footprints while growing business objectives.

Table 1. Model score metrics

Metric	Value
Mean Squared Error (MSE.)	0.00140851909154611
Mean Absolute Error (MAE.)	0.008416912296564199
R-squared (R^2)	0.9857545625642281

The model has predictive solid abilities, reflected in its low MSE of 0.00141 and MAE of 0.00842. That is, on average, how much the prediction varies from the actual emission factor values. This sort of precision is essential in a supply chain context where small changes in emissions at this micro level can have significant environmental implications when multiplied across entire operations. An unusually high R-squared of 0.9858 further underscores the model's effectiveness, showing that it explains nearly 99 percent of the variance in the actual emission factors. Accuracy at this level provides a reliable foundation for decision-makers who base strategic planning and operation adjustments on reduced carbon footprints.

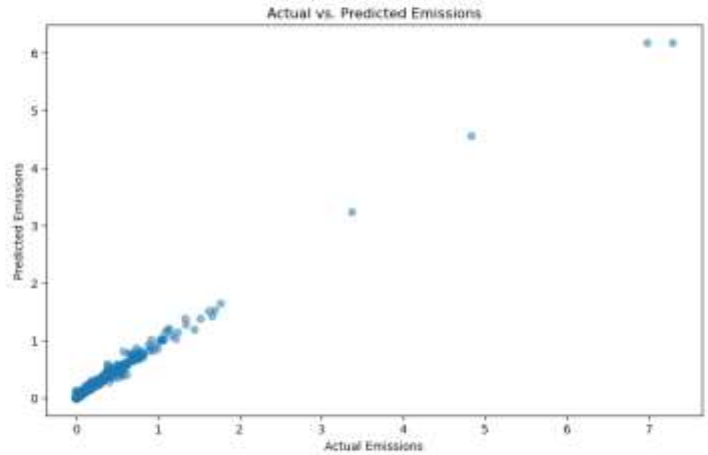

Figure 6. A scatter plot of the predicted versus actual emission factors for model performance

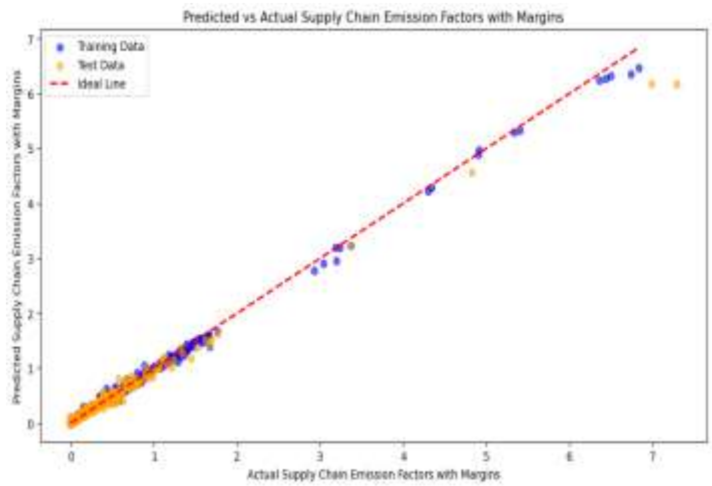

Figure 7. A scatter plot of the predicted versus actual emission factors for model performance tight clustering of the training and test data points along the ideal line

Indeed, Figure 5 shows a scatter plot of the predicted versus actual emission factors for model performance, which alone, through visual analysis, can provide very strong quantitative metrics. The graph shown in Figure 6. of the tight clustering of the training and test data points along the ideal line allows one to visually identify the model's tight consistency for accuracy across different datasets. This is important in revealing its robustness and generalizability characteristics, considering its domains of application.

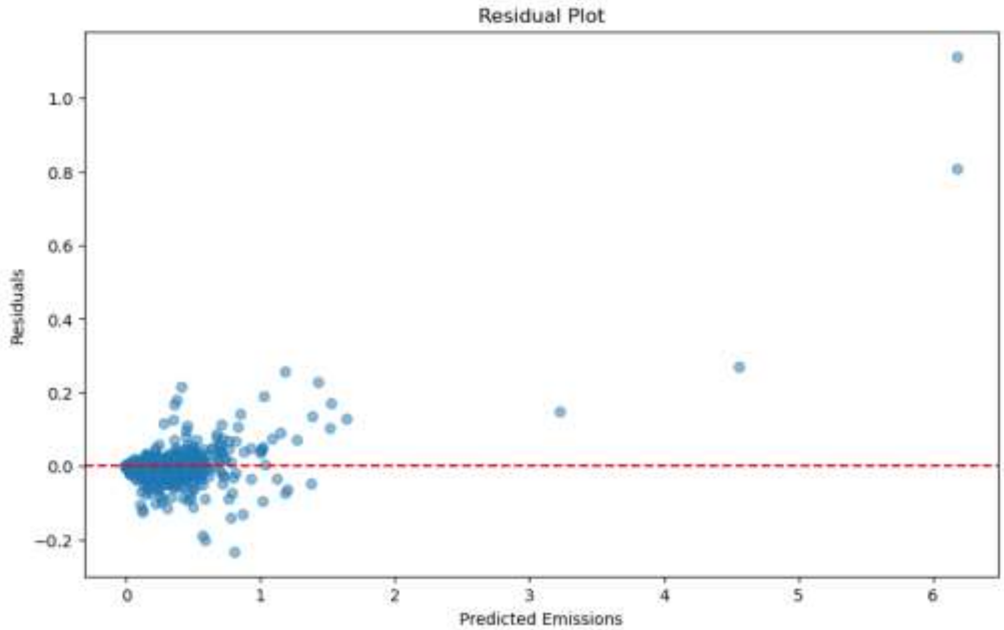

Figure 8. The residual plot is used to further expound on the performance characteristics

The residual plot is used to further expound on the model's performance characteristics. Zero concentration residuals, more for the lower values of predicted emissions, tell that the model's error range was usually small and unbiased for most of the predictions. This would suggest the model's reliability in industries or processes with low emissions profiles—probably a significant share in many supply chains. The increased residual dispersion with higher emission predictions and some rather extreme outliers reflect how model accuracy reduces. This is an essential point for users to reflect upon when applying the model to high-emission scenarios—making the user more conservative about results.

Although the model does not reduce carbon footprints, its high accuracy and predictive solid power open possibilities for potential emission reductions across supply chains. Moreover, the high accuracy of the model gives companies the confidence to pinpoint areas of high emissions in their operations, which can then enable targeted interventions where they have maximum impact, potentially leading to greater efficiency of resource allocation within sustainability efforts. Moreover, the accuracy of models in predicting emissions by various industries and substances may grossly influence the supplier selection process. This will help corporations concentrate on more green partners, hence widening their sustainability beyond immediate company operations.

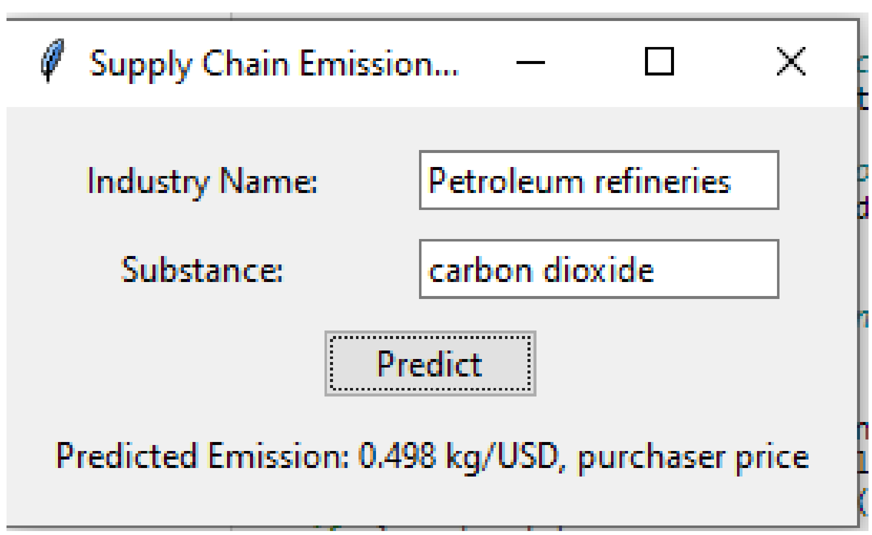

Figure 9. Graphic user interface predicting carbon dioxide emission of petroleum refineries supply chain industry

Moreover, this model provides scope for sophisticated scenario analysis. It can further allow supply chain managers to model different operational configurations in order to accurately estimate in advance the emissions impact of different strategies before their implementation. This will be useful in long-term planning and investment decisions where the choices' environmental implications may not otherwise be obvious. This model provided data-driven decision-making that balanced environmental concerns with other business objectives by providing a reliable projection.

It keeps firms at the forefront regarding compliance accuracy since future environmental regulations are evolving. A reliable tool that could predict these emissions can be instrumental in countries where several governments are rapidly implementing stringent emission standards and reporting requirements. Companies can apply this model to their present standing, project scenarios of their future compliance, and adjust their operations proactively to meet or surpass regulatory expectations.

This proactive stance also means avoiding fines and penalties associated with failing to comply, which involves reputational risks if construed as environmental negligence. The model's contributions to business growth are indirect but huge. Through the model, one can point out avenues for enhancing efficiency in high-emission areas and making cost savings. Such cost savings could be through energy efficiency, resource efficiency, or process efficiencies that are detected through the lens of reducing emissions.

The ability to measure and demonstrably reduce supply chain-related emissions accurately can also be used as a powerful marketing tool: Consumer preferences are increasingly biased towards 'green' companies. Companies can use improved environmental performance, backed by data from the model, to increase market share and attract the increasingly environmentally conscious consumer base.

Such insights from the model can also contribute to innovation within the organization. As companies wrestle with reducing emissions while maintaining or improving operational efficiency, detailed emissions data can impel new product designs, manufacturing processes, and newer supply chain management. Such innovation potential goes beyond efficiency improvements and can lead to new, more sustainable product lines or services. Such innovations can enable new market opportunities and revenue streams, contributing directly to business growth.

On the investor relations side, showing precise control over and insight into supply-chain emissions can make a big difference in a company's attractiveness to investors. Since environmental, social, and governance factors are now important investment considerations, companies demonstrating sophisticated emissions-management capabilities might find an easier path to capital. Such accuracy and comprehensiveness at the model's core could underline transparent reporting and credible sustainability commitments to improve a company's valuation and long-term financial prospects.

Its limitations must be acknowledged to ensure the model is used responsibly and effectively. The more significant residuals observed for the higher emission predictions indicate that accuracy decreases for high-emission scenarios. This limitation needs special care and possibly extra analysis when applying the model to high-emitter industries or processes. Also, the outliers in the residual plot indicate specific cases wherein the model predictions are way off from the actual values. This will determine the nature of these outliers, thus helping improve the model and pointing out particular scenarios unique to emission analysis.

It is worth noting that this model was trained on data up through 2016. Therefore, among the relationships driving model predictions, some may change over time against rapidly moving environmental technology, regulatory framework, and business environment. Temporal limitations of this nature have been brought to users' attention, and they must be prepared to add industry data or trends from more recent years when appropriate.

The predictive model for supply chain emission factors presented herein is accurate and reliable; hence, it is highly effective in supporting companies in reducing their carbon footprint while driving business growth. High predictive power will enable very targeted ways to reduce emissions, allow scenario planning, and deliver data-driven decision-making in a wide range of supply chain management dimensions. The model especially fits in with the growing regulatory pressures and consumer preferences for sustainable business practices, thus repositioning companies to comply with environmental standards and transform their sustainability efforts into competitive advantage.

6. Results

6.1 Key Findings from the Predictive Model

Table 2. Table illustrating critical findings from the created model

Characteristic	Details
High Accuracy	The model demonstrates excellent predictive capability, with a very low Mean Squared Error of 0.00141 and a Mean Absolute Error of 0.00842. This reflects a minimal deviation from actual emission factor values.
High Explanatory Power	The model has returned an R-squared value of 0.9858, which explains almost 99% of the variance in the actual emission factors. This accuracy level forms a reliable foundation for strategic planning and operations adjustment.
Consistency Across Datasets	It is visually depicted with tight clustering of train and test data points against the ideal line through scatter plots, thus asserting the model's robustness and generalizability across diverse industry sectors.
Performance Characteristics	The residual plot shows that the model does excellently when it has low-emission industries or processes. However, the model must improve its accuracy with higher emission predictions, some of which considerably transcend expected predictions.
Temporal Limitation	The historical data was based on 2016, which may not have had recent trends and developments that could influence the reduction of these emissions.

6.2 Relationship between Optimized Supply Chains, Reduced Carbon Footprint, and Business Growth

Table 3. An emitting forecast model can offer benefits such as improved sustainability and business efficiency.

Benefit	Details
Targeted Interventions	This model's high accuracy allows for the confident identification of areas of high emissions. This means that targeted interventions can be planned where they will have the most effect and, therefore, bring efficient resource allocation into sustainability efforts.
Supplier Selection	The model's potential to predict emissions from the industries and substances involved can be most influential during supplier selection processes. In such a case, businesses can engage more with suppliers that demonstrate less environmental impact, hence extending efforts for sustainability beyond the immediate operations of organizations.
Scenario Analysis	Supply chain managers can model a range of operational configurations to estimate the impact of emissions on different strategies before they are implemented in reality. The tool will help drive data-based decision-making that must balance environmental considerations against other business imperatives.
Maintaining Compliance	With this model's precision, companies will be abreast of new and evolving environmental regulations; hence, avoiding fines and penalties will reduce reputational risks related to compliance.
Cost Savings and Efficiency	By pinpointing high-emission areas, the model can drive efficiency improvements and realize significant cost savings through reduced energy consumption and resource utilization.
Market Advantage	Given that consumers are increasingly demanding that the companies they do business with be more socially and environmentally responsible, accurate measurement and reduction of supply chain emissions would be a powerful marketing tool to potentially increase market share.
Innovation Driver	Detailed information on emissions can spur new product design methods, manufacturing processes, and supply chain management that may result in new sustainable product lines or services.
Investor Relations	An organization's ability to show accurate control and understanding of the source of emissions in its supply chain makes it attractive to investors, especially since ESG considerations take center stage in investment decisions.

6.3 Case Study Analysis

The following example uses two hypothetical industries—electronics manufacturing and food processing—to illustrate how predictive modeling can apply these supply chain emissions factors. In the electronic manufacturing industry, with highly complex global supply chains and several tiers of suppliers, the model would probably identify that a large part of the emissions is from producing specific components, particularly batteries and displays. Such a view would enable the company to re-engineer products with cleaner components, collaborate with suppliers in cleaner production, and redesign its transport route structures to lower CO_2 emissions from logistic activities. This may yield lower carbon footprints, less costly productions, and higher brand values by exploiting new market segments with eco-friendly product lines that appeal to environmentally conscious consumers.

In contrast, companies involved in food processing may have flatter emission profiles along their supply chains—from agriculture to processing and distribution. Equipped with the predictive model, such a food processing company could identify high-emission ingredients and be able to provide alternatives or ways of engaging farmers in more sustainable practices, optimize processing techniques to reduce energy consumption, adopt more efficient methods of packaging and distribution, and so on. Such changes can reduce emissions, lower operating costs, and better product quality. Therefore, the company will claim to have environment-friendly products, thus commanding premium prices and gaining market share among health- and environment-conscious consumers.

The two industries would benefit from an improved ability to quantify the reductions in their emission through better substantiation of marketing claims and regulatory compliance. This would help entities decide on capital investment in cleaner technologies and attract environmentally conscious investors and green financing options. Notably, however, the model has its limitations: notably, it could be more accurate for high-emission scenarios and based on historical data up to 2016. This implies that companies should use current trends in the industry and emerging technologies to have holistic emission reduction and growth plans in supplement to insight given by the model.

7. Discussion

AI and predictive analytics integrated into SCM mean a significant jump in operational efficiency and decision-making prowess. This has important implications for companies through the proposed model, which predicts the supply chain emission factors to strive and optimize operations with reduced environmental impact. According to Toorajipour et al. (2021), AI-driven insightfulness has improved resource efficiency and reduced costs while bettering sustainability. This is reflected in the high degree of accuracy at which the model predicts emissive factors from industry to industry, guaranteeing that targeted interventions will make a difference. One significant advantage is that integrating AI with predictive analytics in SCM brought improved forecasting. Lamba and Singh comment that technologies of this nature can improve demand forecasting accuracy, making inventory management possible and reducing wastage. In other words, it will make a proposed model understand the causative factor of an emission well in advance for mitigation.

According to Baryannis et al. (2019), AI helps reduce associated risks by detecting possible supply chain disruptions ahead of the actual event. Within this framework of environmental sustainability, this proactive dimension of risk management becomes very useful since any unplanned increase in disruption might dramatically raise emissions. Among the significant conclusions put forth by the proposed model is that AI-driven S.C.M. holds enormous potential for optimizing sustainability. Bag et al. (2020) state that big data analytics can improve sustainable supply chain performance. This is evident from the model's emission factor prediction capability, which has further guided decision-making toward more sustainable business practices. Consiis increasing regulatory pressures and consumer preference toward green business practices may be an essential competitive advantage for firms.

Despite all the odds, the potential benefits of integrating AI and predictive analytics in SCM for sustainability are huge. To successfully implement similar strategies, businesses should consider several key recommendations. First and foremost, companies must invest in a robust data infrastructure. Wang et al. (2016) point out that proper data collection and management systems have to be developed across the supply chain so that high-quality data can be procured consistently. This forms the base for any AI-driven initiative within SCM.

Another critical factor is the development of cross-functional expertise. Brinch et al. (2018) support building relevant teams with combined expertise in SCM, data science, and sustainability. Only such an interdisciplinary approach will be able to bridge the gap between technical model development and the business application domain by ensuring that AI-driven insights can turn into real strategies for sustainability improvement.

Dolgui et al. (2020) recommend starting pilot projects to this end. Starting with small areas of implementation to test how effective AI and predictive analytics are within the supply chain would bring in a lot of valuable lessons learned and refinement of the approach before scaling up. Such an iterative process would be able to ward off associated risks and ensure a smoother full-scale implementation.

Success in organizational change—of any kind—will require buy-in from stakeholders. Queiroz and Wamba (2019) underline the importance of educating primary stakeholders, mainly top management-level stakeholders, on the implementation process to ensure proper alignment within the organization regarding AI-driven sustainability initiatives.

Notably, model updating and validation are supposed to be done constantly to maintain relevance and accuracy. Wamba et al. (2020) indicate that a model should be patently updated as new data becomes available, and the model is validated concerning its performance due to changes in the business environment and changes in technology. This process will continue so the models remain useful for insights and decision-making.

In this respect, ethical considerations have to be also associated with AI in S.C.M. Ivanov and Dolgui (2020) raise awareness about the ethical use of AI, particularly regarding data privacy and the effect this might have on workforce dynamics. Sustainability efforts through AI should be relevant to moral and social goals and have to be aligned for long-term success.

Finally, seamless integration with existing systems is key to maximizing efficiency and minimizing disruption. As Dubey et al. explain, it is exceedingly important to ensure that new AI-driven tools work harmoniously with existing SCM systems. This will help integrate them into a coherent and data-driven supply chain management and sustainability approach.

Thus, even though integrating AI and predictive analytics in SCM for sustainability is a huge challenge, the potential benefits, such as improved efficiency, reduced environmental footprint, and competitiveness, make this something that forward-looking businesses would want to pursue.

8. Conclusion

The research results prove that AI and predictive analytics can significantly help supply chain management achieve sustainability and business growth. The model designed while predicting supply chain emission factors yields high accuracy and reliability, as characterized by a low Mean Squared Error of 0.00141 and an outstanding R-squared value of 0.9858. These results demonstrate the model's capacity to provide highly accurate insight into environmental impacts across industries and substances.

AI and predictive analytics in supply chain management are strong drivers of sustainable business growth. They help companies efficiently balance environmental concerns and business-related objectives by accurately identifying high-emission areas, facilitating scenario analysis, and data-driven decision-making. The model's ability to guide targeted interventions for reducing emissions yet potentially discover cost-saving opportunities illustrates the interaction of sustainability efforts and business growth.

The following would be the directions in this research during its future:

a) By integrating real-time data streams into the model, the model will become more accurate and responsive to rapid market changes.
b) Investigating the integration of blockchain technology to achieve transparency and traceability within sustainable supply chains.
c) Deep learning techniques must be examined for their application in modeling complex data patterns on emissions.
d) Model designs to forecast and optimize several sustainability metrics simultaneously beyond emission factors.
e) Long-term economic impact analysis of AI-driven sustainability initiatives on business performance and market competitiveness.

As the domain evolves, we can expect more sophisticated integrated systems that can provide holistic views of supply chain sustainability, helping businesses make effective decisions that balance environmental responsibility with economic growth.

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