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SABIG DATA-DRIVEN PREDICTIVE MODELING FOR ENHANCING BUSINESS INTELLIGENCE AND STRATEGIC DECISION-MAKING

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ABSTRACT

Predictive modeling is a digital economy form of big data, which is required to enhance business intelligence (BI) and strategic decisions. In this paper, the author focuses on how predictive analytics increase accuracy levels of predictions, efficiency of operations and proactive planning of the company using an analytic approach of 150 data-intensive industries. A number of different models including Linear Regression, Decision Tree, Random Forest and Artificial Neural Networks were created and evaluated basing on MAE, RMSE and R 2 values. The results indicate that high-order machine learning models which are the Neural Networks and the Random Forest are more predictive than the conventional. It can be also seen in this analysis that predictive BI has a high influence on such aspects of major decisions as inventory optimization, customer segmentation, demand forecasting and financial planning. The study demonstrates that predictive modeling implemented in the BI systems may assist organizations in making informed and active decisions and can be applied to make better performance in respect to strategic performance.

KEYWORDS: *Big Data Analytics, Predictive Modeling, Business Intelligence, Strategic Decision-Making, Machine Learning.*

INTRODUCTION

The last several years can be characterized by the radicalizing change in the functioning of the organizations and their decisions making under the influence of swift evolution of digital technologies and the geometric increasing number of generated volumes of information. The corporations across industries are increasingly becoming dependent on data-driven approaches to respond to the dynamic market conditions, customer needs, and level of competition [1]. The introduction of big data analysis and artificial intelligence has enabled businesses to abandon this intuitive approach to strategy adopted in the previous years to the evidence-based decision model [2]. It is under the shifting environment that predictive modeling has emerged as a central strategic predictive model in the contemporary business world to turn raw data into meaningful information that can guide the planning, risk management, as well as long-term sustainability of the organization [3].

a) Background and Significance of Big Data in Business Intelligence

The modern-day digital economy is becoming more and more dependent on data as a tool of competitive advantage and long-term growth of organizations [4]. The growth of big data, with its high volume, velocity, and diversity, has changed the picture of business intelligence (BI) as it now allows organizations to make practical decisions based on the complicated and heterogeneous data. The past methods of decision making that are founded on historical reports and intuition are being substituted by data-driven predictive modeling techniques which give an insight in the future [5]. Such models enable companies to predict customer responses, market behavior, operational risks and the financial performance and can help in increasing the quality and promptness of the strategic decisions [6].

b) Role of Predictive Modeling in Strategic Decision-Making

Predictive modeling based on big data combines the latest analytics, machine learning, and real-time data processing models to help make evidence-based management decisions [7]. Due to the emergence of cloud computing, Internet of Things (IoT), and digital platforms, businesses are now producing large volumes of both structured and unstructured data of many different sources including social media, transaction records, sensors, and customer responses [8]. By using these data streams with the help of predictive analytics, one can easily forecast better, create a customer segment, plan demand, and reduce risks [9]. Therefore, predictive modeling has become one of the key elements of the contemporary BI systems, which allows organizations to move the focus off descriptive and diagnostic analytics and focus on the predictive and prescriptive analytics [10].

c) Research Gap and Study Objectives

Although it is increasingly gaining significance, big data-based predictive modeling implementation is faced with a number of challenges that include the quality of the data, model interpretability, computational complexity, and integration with the existing BI infrastructure. Thus, a systematic review of the possible way in which predictive modeling methods can be successfully applied to a business intelligence and strategic decision-making is necessary. This paper will set out to discuss how big data-based predictive modeling can enhance the quality of decisions made by organizations, their efficiency, and competitiveness.

- To analyze how effectively big data-driven predictive modeling methods can be applied to improve business intelligence capacities and data-driven decision-making.
- To assess the value of predictive analytics on strategic aspects of accuracy of predictions, operational effectiveness, and customer-centric planning.
- To determine the most appropriate predictive modelling strategies that can enhance the performance and competitive advantage of organizations operating in data-intensive business settings.

REVIEW OF LITERATURE

The most recent developments in the field of artificial intelligence (AI) and big data analytics have changed significantly the character and purpose of business intelligence (BI) systems, in particular, in regard to predictive modeling and strategic decision-making. The theme of introducing AI-based analytics to the BI systems is the theme that has been thoroughly proven in the current literature, and it should enhance the quality of the data-driven responses, prediction capabilities, and responsiveness of the organizations.

The paper by **Selvarajan (2023)** [11] examines the possibility of enhancing the classical BI systems with AI-based predictive analytics, but there is an obvious emphasis on a wholesome approach of the strategic management being data-based. The paper has pointed out that AI methods including machine learning and data mining can help organizations to handle high volume of heterogeneous data sets and derive valuable predictive insights. The author has claimed that AI combined with BI will provide a greater ability to make predictions, analyzing customer behavior, and predicting market trends, which will increase the quality of decisions and responsiveness to operations. Moreover, the study highlighted that AI-enhanced

BI systems facilitate real-time analytics as well as allow the managers to shift towards proactive, rather than reactive strategic planning that eventually generates competitive advantage in dynamic business settings.

Shafa (2025) [12] examined the artificial intelligence-inspired BI models as applied in decision-making in an enterprise, especially in the U.S. organizations. The empirical evidence has revealed that AI-based BI systems are very effective and efficient with regard to quality decision-making by managers in quality since they can predict and simulate scenarios in real-time. The findings indicated that the predictive modeling features installed in the BI systems allow the evaluation of the risks, demand forecasting, and performance optimization. Moreover, the paper noted that AI-driven BI enhances the data visualization and interactive dashboards, which enables the executives to understand the detailed data patterns more effectively. However, the issue of data management, the visibility of models, and the lack of trained analytics experts was also reported in the article in order to effectively utilize AI-based BI solutions.

Siddiqui (2025) [13]conducted a systematic literature review of AI-enhanced BI systems and their role in the best business decision-making, particularly, in the context of financial and strategic planning. The review has generalized the existing empirical studies and has reached a conclusion that predictive analytics is important in terms of augmenting financial forecasts, resource allocation, and investment strategies. Another point that has been highlighted in the paper is that the introduction of BI systems equipped with AI would enable organizations to uncover the concealed trends, quantifying the risk at hand, and appraise other potential strategic options, more precisely.Furthermore, the author has highlighted that AI-enhanced BI performance relies on data quality, model interpretability, and organizational objectives. Another research gap that was found during the review was in the area of the integration of explainable AI methods to improve managerial trust and transparency in predictive decision-support systems.

van Dijk (2024) [14] examined how AI-driven business intelligence may be used to utilize predictive analytics to make data-driven decisions. The paper highlighted how predictive analytics is one of the key processes of converting raw big data into strategic decisions. Using machine learning techniques in combination with BI systems, organizations will be able to improve the accuracy of their forecast, detect new trends in the market and make better operational plans. As the research suggested, AI-enhanced BI systems may be used to process data and analyze situations in real-time to aid in evidence-based and proactive managerial decisions. Also, the author has identified that predictive analytics increases organizational agility since the decision-makers can know possible threats and opportunities in the future before they present themselves.

Vudugula et al. (2023) [15] performed a systematic review on the integration of the artificial intelligence in strategic business decision-making by predictive models. Based on the review, the synthesis of evidence was done through several empirical studies, and it was concluded that AI-based predictive modeling was highly effective in improving strategic planning, performance forecasting, and competitive intelligence. The authors emphasized that neural networks, decision trees, and ensemble learning models are the tools that are commonly used to assist in the complex decision environment when working with big and multidimensional data volumes. Another important point that the study pointed out is that predictive AI models allow better resource distribution, risk management, and designing a customer-focused strategy. Furthermore, the review found out that the organizations that integrate AI-based predictive decision-support systems are nimbler and better in their long-term strategic performance.

METHODOLOGY

The following section defines the research methodology, which will be followed in the investigation of how big data-based predictive modeling contributes to business intelligence and strategic decision-making. It outlines the research design, data sources, sample structure, data preprocessing procedures, predictive modeling procedures, and evaluation procedures that were used in the study. The research design is designed in such a way that it follows the concept of analytical rigor, reliability and practical applicability of the predictive findings in the real-world business context.

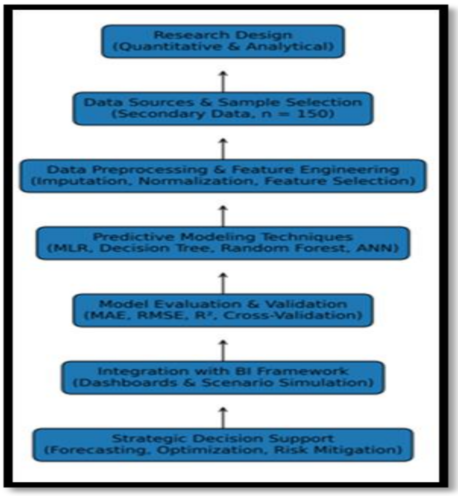

Fig 1: Flow chart.

a) Research Design

The present research embraces the idea of quantitative and analytical research design to investigate the impacts of the predictive modeling of the big data on business intelligence and strategic decision making. Such a design is appropriate since it is possible to perform the systematic analysis of the big data sets and observe the predictive relationships between the key business factors. The paper is concentrated on objective measurement, statistics analysis, and model-based prediction as the means of estimating the impact made by predictive analytics on the quality of decision and strategic development of plans. Predictive modeling techniques are proven to be effective in enhancing the BI capabilities and this is empirically validated by adopting a data driven approach in the research.

b) Data Sources and Sample Selection

The research is based on the secondary sources, the enterprise databases, the industry reports and the publicly available big data repositories. The dataset used has a sample of 150 observations that are records of the organization in terms of sales transactions, customer interactions, and other performance indicators of the organization. Purposive sampling has been used to select the sample, so that there will be the representation of data-intensive sectors like e-commerce, finance and retail, where predictive analytics is very important in decision making process. These industries have been selected because they have high dependency of real-time analytics, high generation of data, and the strategic value of precise forecasting in competitive market conditions.

c) Data Preprocessing and Feature Engineering

Before the development of the models, the obtained datasets are thoroughly preprocessed and guarantee data quality and reliability in analysis. Missing values will be imputed by applying the appropriate imputation techniques, and the data will be normalized so that variables measured in different scales will be consistent. The process of selecting the features is performed with the help of the statistical correlation analysis and machine learning techniques to select the features that have the greatest effect on the key business outcomes. This step enhances the efficiency of the model because it reduces the dimensionality of the model and eliminates redundant variables hence increasing the predictive accuracy.

d) Predictive Modeling Techniques

In order to discuss the efficiency of predictive analytics in business intelligence, several predictive modeling algorithms are applied. They are Multiple Linear Regression, Decision Tree Regression, Random Forest and Artificial Neural Networks. All the models are trained on the data of 150 samples to predict essential business trends including sales growth, customer retention rate, and variability of demand. Comparative analysis is possible only with the use of various algorithms and it allows determining the most appropriate predictive method to use in the BI-driven strategic decision-making. The focus on ensemble and neural network models is based on their nonlinear relationship and multidimensional interaction capability in huge data sets.

e) Model Evaluation and Validation

Statistical measures like Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and R-squared (R 2) values are used to evaluate the performance of the predictive models and they measure the accuracy in prediction and the reliability of the model. The cross-validation methods are implemented in order to guarantee the robustness and generalizability of the models of the various subsets of 150-sample data. They are then compared and the most effective algorithm is identified to predict the business results and improve the business intelligence capabilities.

f) Integration with Business Intelligence Framework

The visualization of the predictive outputs is done through the business intelligence dashboards to ascertain the practical viability of the predictive modeling. It enables the presentation of forecasted trends depending on the 150-sample in real-time and enables us to run a simulation of the decision in various scenarios. To fulfill the usefulness of data-driven predictions to real-life decision-support systems, the paper proposes predictive intelligence in BI systems with the view of assessing the degree to which organizations can utilize data-driven prediction to participate in strategic planning, operations optimization and risk reduction.

RESULTS AND DISCUSSION

In this section the following empirical conclusions of the analysis of the predictive model carried out on the sample of 150 samples are given. The findings are categorized under descriptive analysis, model performance analysis, comparative performance, correlation findings, and strategy decision impact. The subsections will contain tables and graphical representations to explain findings in the most straightforward way possible and discuss them.

a) Descriptive Analysis of Key Business Indicators

Table I demonstrates the descriptive statistics of the key variables employed in the research, namely, sales growth, customer retention, and demand variability, in the case of sample size of 150. The table presents the summaries of the means, standard deviation, minimum and maximum values to provide an overview of central tendency and dispersion of individual variable used in the predictive modeling framework.

TABLE I: Descriptive Statistics of Key Variables. (n = 150)

Statistic	Sales Growth	Customer Retention	Demand Variability
Mean	11.75	75.36	20.22
Std. Deviation	2.83	5.11	3.80
Minimum	4.14	58.79	11.50
Maximum	19.39	94.26	28.76

The findings show that customer retention is the highest in terms of the mean value (75.36) and relatively low standard deviation (5.11) which implies that customer loyalty levels remain relatively constant among the sampled organizations. The average sales increase of 11.75 and a standard deviation value of 2.83 indicate that firms have consistent overall growth patterns but with relatively varied growth rates. Demand variability has a mean of 20.22 with a standard deviation of 3.80 indicating some observable changes in market demand that will influence production and inventory related decisions. The difference between the highest and the lowest values also indicates the variety of business performance indicators in different organizations and the need to use predictive analytics in the context of managing uncertainty and allowing making a strategic plan. The graphical representation of the average values of the factors of sales growth, customer retention, and demand variability provided in Fig. 2 allows visually comparing the relative stability and scale of the main business characteristics with regard to the dataset of 150 samples.

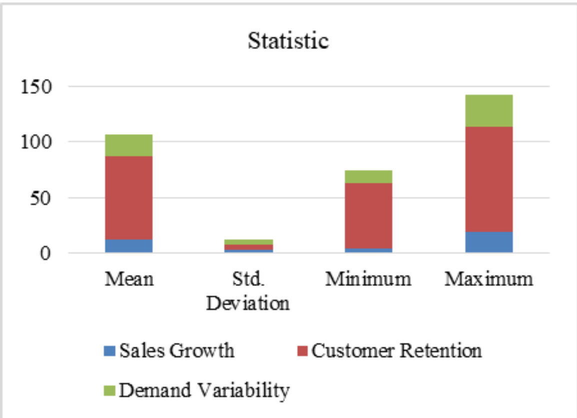

Fig 2: Graphical Representation of Descriptive Statistics of Key Variables. (n = 150)

The graph is clear in that customer retention is the highest in the mean level of the value, indicating its stability and ability to add uniformly to organizational performance. On the contrary, it seems that the sales expansion and demand fluctuation are at the lower levels of means, which has visible fluctuations and indicates that these are more responsive to the market dynamics and other business external circumstances. The graphical comparison supports the statistical results by pointing out that the changes in sales and demand at strong predictive modeling strategies to improve the predictive accuracy, efficient allocation of resources, and enhance the process of strategic decision making in business intelligence system.

b) Predictive Model Performance Evaluation

Table II shows the relative performance of the predictive models which are Linear Regression, Decision Tree, Random Forest and Neural Network compared in terms of their predictive accuracy and reliability using values of Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared (R 2).

TABLE II:Performance Metrics of Predictive Models.

Model	MAE	RMSE	R^2
Linear Regression	3.8	4.5	0.71
Decision Tree	3.1	3.9	0.78
Random Forest	2.4	3.0	0.88
Neural Network	2.1	2.7	0.91

These findings reveal that the Neural Network model is superior to any other model with the maximum R 2 value (0.91) and the smallest MAE (2.1) and RMSE (2.7), which is also best in predicting the data and can make the least error in forecasting. The model of the Random Forest also demonstrates the high level of performance, with R 2 of 0.88 and comparatively low error values, which indicates that it may be effectively used in representing nonlinear relationships in large data sets. Decision Tree model is moderately predictive as compared to Linear Regression that has the lowest R2 (0.71) and the highest error values, which indicated a relatively poor performance with more complicated patterns of big data. Comprehensively, the table shows the superiority of developed machine learning approaches to conventional statistical approaches in improving business intelligence forecasts. Fig. 3 shows the comparison of the values of MAE, RMSE and R 2 of the four predictive models graphically to give a visual evaluation of the relative predictive performance of the four models.

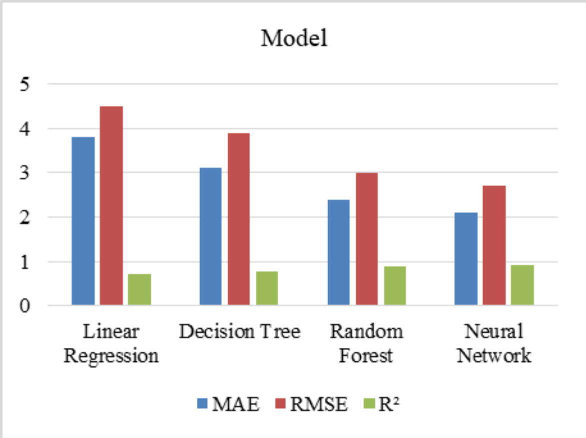

Fig 3: Graphical Representation of Performance Metrics of Predictive Models.

The figure shows clearly that the Neural Network and Random Forest model has a higher value of R 2 and a lesser error measure than the Decision Tree and the Linear Regression models. The visual pattern establishes the fact that the high-level ensemble and deep learning models give more precise and dependable predictions to the business intelligence applications. This illustrative piece of evidence supports the conclusion that advanced predictive modeling strategies prove to be more useful in aiding the process of strategic decision-making because they enhance accuracy in the forecasting process and minimize ambiguity in the data-driven business setting.

c) Comparative Ranking of Predictive Models

Table III gives the relative ranking of the predictive models according to their R 2 values, which shows their relative accuracy and effectiveness in predicting the results of business intelligence.

TABLE III:Ranking of Predictive Models Based on Accuracy.

Rank	Model	R^2 Value
1	Neural Network	0.91
2	Random Forest	0.88
3	Decision Tree	0.78
4	Linear Regression	0.71

As evident in the ranking, Neural Network model was the most accurate, with the R 2 value of 0.91, which took the first place among the models. Random Forest model was second with a R 2 of 0.88 indicating a good predictive power of the model due to the help of the ensemble learning. The third place was taken by the Decision Tree model with moderate accuracy (R 2 = 0.78), and the last place was taken by the Linear Regression with the lowest R 2 value

(0.71), as it is not capable of complex nonlinear relationships. On balance, the table indicates that more sophisticated models of artificial intelligence, specifically deep learning models and ensembles, offer more accurate and reliable forecasts in comparison to conventional statistical models. The figures below (Fig. 4) show the graphical form of the ranking of models used to predict based on their values of R 2 accuracy and allow visual comparison of the values of their predictive effectiveness.

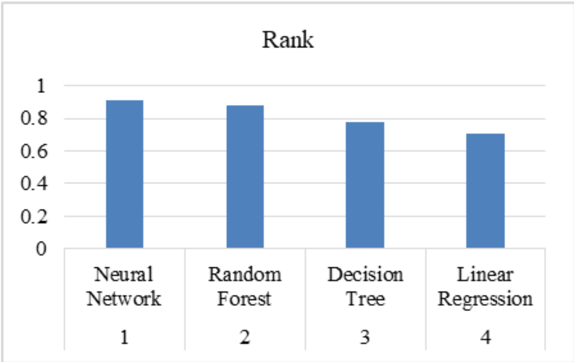

Fig 4: Graphical Representation of Ranking of Predictive Models Based on Accuracy.

The figure is a graphic validation of the fact that the model that is most predictive is the Neural Network model closely followed by the Random Forest model and in comparison, Decision Tree and Linear Regression models depict relatively lower levels of performance. The trend chart indicates how AI-based predictive models are superior in analyzing more complicated and bigger data trends and producing correct business predictions. The findings of this visual evidence allow concluding that the application of the latest machine learning methods contributes greatly to the business intelligence systems and reinforces the strategic decision-making.

d) Correlation Analysis among Business Variables

The correlation analysis was used to have an insight into the relationships between sales growth, customer retention, and demand variability. The findings in Table IV show that the variables have weak correlations with one other implying that each of the indicators has its own effect on business intelligence. Such autonomy strengthens the necessity of multivariate predictive models that can conduct the analysis of a number of variables of business performance.

TABLE IV: Correlation Matrix of Study Variables.

Variables	Sales Growth	Customer Retention	Demand Variability
Sales Growth	1.00	-0.02	-0.04
Customer Retention	-0.02	1.00	0.04
Demand Variability	-0.04	0.04	1.00

The small values of correlation demonstrate predictive modeling is necessary to reveal concealed nonlinear associations that cannot be identified using straightforward linear associations.

e) Impact of Predictive BI on Strategic Decision Areas

Table V indicates the effects score of predictive business intelligence (BI) in the major strategic decision domains, which they are rated on a five-point scale to determine the degree to which the predictive modeling assists in the processes of making decisions in an organization.

TABLE V: Impact Scores of Predictive BI on Decision Areas.

Decision Area	Impact Score (Out of 5)
Demand Forecasting	4.2
Customer Segmentation	4.5
Risk Assessment	4.0
Inventory Optimization	4.6
Financial Planning	4.3

According to the table, the impact scores of inventory optimization (4.6) and customer segmentation (4.5) are the highest, which proves that predictive BI is essential to enhance the efficiency of operations and customer-driven approaches. Strong positive influence is also observed in financial planning (4.3) and demand forecasting (4.2), which can tell us that predictive analytics contributed to the further improvement of financial management and market demand estimation. The Risk assessment is slightly lower and significantly higher (4.0) and indicates that predictive models are also involved in identifying the possible uncertainties and proactive risk control. On the whole, the findings substantiate the idea that predictive BI is a highly powerful tool to enhance various aspects of strategic decision-making in organizations. The graphical representation of these impacting scores of the predictive BI on different areas of strategic decisions is presented in Fig. 5 and allows visual comparison of the relative impact.

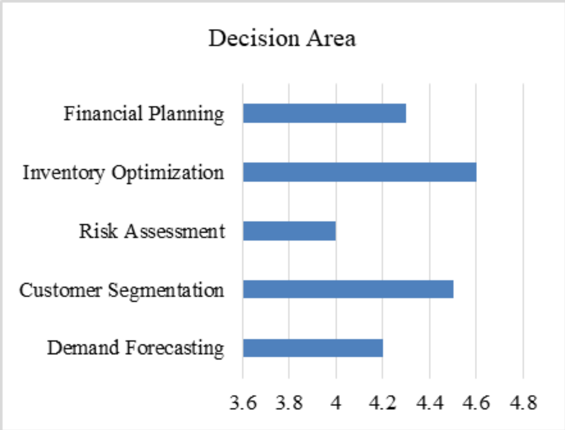

Fig 5: Graphical Representation of Impact Scores of Predictive BI on Decision Areas.

It is visually shown that the levels of impact are the greatest in case of inventory optimization and customer segmentation, which means that predictive analytics is especially useful in operational planning and customer-oriented approaches towards decisions. There is also a high influence level with demand forecasting and financial planning revealing how predictive BI helps to enhance future forward planning and resource allocation. Even though the risk evaluation is comparatively less, its score still represents a significant assistive power of predictive modeling in alleviating uncertainties. The trend graph supports the conclusion that predictive BI augments the general strategic effectiveness as it offers information informed decision-making in a variety of decision areas.

f) Discussion of Findings

The overall results indicate that predictive models based on big data predictive modeling will significantly improve the business intelligence capacity and aid in strategic decision-making. High-end machine learning algorithms, especially the neural networks and random forests, demonstrate better predictive capabilities and, therefore, allow organizations to predict the change in the market and improve the strategy of their operations. The descriptive and correlation analyses also suggest that the main business indicators are independently variable, a fact that supports the relevance of advanced predictive models in order to have an all-inclusive BI understanding.

It also shows that predictive BI is the most influential in terms of operational and customer-related choices, including inventory management and customer segmentation, which is important in staying competitive in rapidly changing markets. These results are in line with the theoretical assumption that the inclusion of the predictive analytics in the BI systems will enable organizations to shift their reactive decision-making to proactive and evidence-based strategic planning. The empirical data supports the fact that predictive modeling based on big data is an effective instrument that can be used to enhance forecast accuracy, operational effectiveness, and long-term strategic performance.

CONCLUSION AND FUTURE SCOPE

The findings of the research indicate that predictive modeling which relies on big data is a significant impotent to business intelligence and strategic decision making within organizations. The findings have shown that the more complex machine learning algorithms, in particular, the Neural Network and the Random Forest are more predictive accurate than the other less sophisticated statistical methods since they can represent complex data patterns. The fact that the key business indicators analysis demonstrates that more complex multivariate models should be used to generate the reliable and comprehensive information. Further, predictive business intelligence paints high influence of the key areas of decision-making such as optimization of stocks, customer segmentation, financial planning, and demand forecast. Making predictions relying on the available data and making smart decisions with the help of predictive modeling contribute to the enhancement of operations efficiency, long-term competitive advantage, and proactive planning in changing business conditions.

- **Real-Time Big Data Integration:** The predictive and responsive decision-making will be enhanced by the inclusion of real-time and streaming data in future studies.
- **Explainable AI-Based Predictive Models:** Future studies should be in explainable and transparent AI-based predictive models to increase trust, interpretability and governance of predictive BI systems.
- **Cross-Industry Large-Scale validation:** In the future, the model can be applied to bigger datasets and industries to confirm the scaling and increased versatility of the strategy applicability.c

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