Optimizing Business Intelligence and Operations Research for Sustainable Growth: A Comparative Study of Manufacturing and Service Industries

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Abstract

This paper presents a comparative study of two optimization techniques, business intelligence (BI) and operations research (OR), for achieving sustainable growth in manufacturing and service industries. The study explores the strengths and weaknesses of both techniques and examines their suitability for addressing sustainability challenges in these industries. The paper also discusses various factors that influence the choice of optimization technique and presents a framework for selecting the most appropriate technique based on the problem domain, data availability, and organizational requirements. The study concludes that both BI and OR have significant potential for improving sustainability in manufacturing and service industries, and their effectiveness depends on the problem domain and organizational context. The paper provides valuable insights for researchers and practitioners interested in leveraging optimization techniques for sustainable growth.

Keywords: Business Management; Operation Research; Industry 4.0; Smart Manufacturing

1. Introduction

Business intelligence (BI) refers to the process of analyzing large amounts of data to gain insights into business operations and make informed decisions. In today's rapidly evolving business landscape, sustainability has become a crucial factor for long-term success. BI plays a critical role in achieving sustainable growth by providing organizations with a comprehensive understanding of their operations, customers, and markets. By leveraging data-driven insights, companies can identify areas of improvement, streamline processes, optimize resource allocation, and respond quickly to changing market conditions. Moreover, BI can help organizations identify opportunities for innovation and stay ahead of their competitors. Ultimately, the ability to make informed decisions based on data is essential for organizations seeking to achieve sustainable growth and create long-term value for all stakeholders.
Operations research (OR), also known as management science, is the application of mathematical and analytical methods to complex business problems. It involves the use of quantitative models to optimize processes, make informed decisions, and improve efficiency. For organizations seeking sustainable growth, OR is essential for several reasons. First, it can help companies identify opportunities for cost reduction, resource optimization, and process improvement. By using data-driven insights to streamline operations, organizations can reduce waste, increase productivity, and improve their bottom line. Second, OR can help companies navigate complex and uncertain business environments by providing a framework for decision-making that is based on rigorous analysis and modeling. This can help organizations make better decisions and reduce the risks associated with uncertain or unpredictable outcomes. Ultimately, OR is critical for organizations seeking to achieve sustainable growth by leveraging data and analytics to make informed decisions and optimize their operations.

Doi: https://doi.org/10.54216/AJBOR.050104
Received: July 11, 2021 Accepted: September 29, 2021

1.1. Research gaps

Several research gaps motivate researching BI and operation research for sustainable growth in the industry. First, In the field of manufacturing industries, there is a need for research on how BI and OR can be used to achieve sustainable growth in specific sectors such as automotive, food processing, and chemical manufacturing. For instance, research can be conducted to identify the key performance indicators that should be tracked to optimize production processes, minimize waste, and reduce environmental impacts. Moreover, research can be done on how to integrate sustainability considerations into supply chain management to improve efficiency and reduce costs. Similarly, in the service industries, research can be conducted to understand how BI and OR can be used to achieve sustainable growth in sectors such as healthcare, education, and tourism. For instance, research can be done on how data analytics can be used to improve patient outcomes and reduce healthcare costs. Moreover, research can be done on how to optimize energy consumption in educational institutions to reduce environmental impacts and save costs. Additionally, research can be done on how to leverage data to enhance customer experiences in the tourism sector while minimizing the environmental impacts of tourism activities. Regarding organizational culture, research can be done to understand how to foster a culture of sustainability in manufacturing and service industries. For example, research can be conducted to identify the organizational factors that facilitate or hinder the adoption of sustainable practices, such as the role of leadership, employee engagement, and organizational learning. Finally, regarding the impact of digital transformation, research can be done to understand the potential benefits and challenges of using emerging technologies such as artificial intelligence, machine learning, and the Internet of Things for sustainable growth in manufacturing and service industries. For example, research can be done to identify the key success factors for implementing digital transformation initiatives that promote sustainability, such as data security, privacy, and ethical considerations.

1.2. Aims and Contributions

This paper is motivated by the need for organizations in both manufacturing and service industries to achieve sustainable growth. With increasing competition and changing customer preferences, companies need to constantly improve their operations and decision-making processes to remain successful in the long run. BI and OR are two widely used methodologies that can help organizations achieve this goal, but there is still a need to understand which approach is best suited for different types of businesses. We aim to provide a comparative study of BI and OR and their effectiveness in achieving sustainable growth in manufacturing and service industries. Then, we highlight that while BI focuses on using data analysis to gain insights into business operations aiming to optimize decision-making processes using mathematical models. By comparing these two approaches, we aim to provide insights into which methodology is best suited for different types of businesses and under what conditions. Our framework highlights the importance of sustainability in business operations and emphasizes that achieving sustainable growth is crucial for businesses in the long run, not only for environmental and social reasons but also for economic reasons. By using BI and OR to optimize their operations, businesses can reduce waste, increase efficiency, and improve their bottom line. We aim to provide insights into how BI and OR can be used to achieve sustainability goals in both manufacturing and service industries, and how these goals can be aligned with overall business objectives.

1.3. Organization

The remaining parts of this study are planned as follows. First, the literature is reviewed in Section 2. The methodology of our research is explained in section 3. The results are presented in section 4. Then, we discuss the experimental findings and observations in section 5. The conclusions are derived in section 6.

2. Literature Review

This section provides an insightful review of the literature on BI and OR and their applications in the manufacturing and service industries based on a critical analysis of the existing research in the field. In [1], Lopes de Sousa Jabbour et al. proposed a research agenda and roadmap for integrating Industry 4.0 technologies with the circular economy to promote sustainable operations, thru improving resource efficiency, waste reduction, and economic competitiveness. In [2], Kumar et al. provided a review of the application of multi-criteria decision-making (MCDM) techniques in the context of sustainable renewable energy development. They then reviewed various MCDM techniques, such as Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and Multi-Attribute Utility Theory (MAUT), that can be used to make complex decisions in renewable energy

Doi: https://doi.org/10.54216/AJBOR.050104
Received: July 11, 2021 Accepted: September 29, 2021

development. In [3], Liu and Xu compared Industry 4.0 and cloud manufacturing in terms of their similarities, differences, and potential for integration. They explored the two concepts in terms of their architecture, technology, applications, and challenges. They concluded that while there are some differences between Industry 4.0 and cloud manufacturing, both concepts share a common goal of enabling flexible, efficient, and intelligent manufacturing. In [4], Gupta et al. provided an overview of a multi-year model curriculum development effort for teaching business intelligence and big data in higher education. The authors discussed the importance of data-driven decision-making in today's business environment and the need for educational programs to prepare students with the necessary skills and knowledge. They then describe the development process of the model curriculum, which involved input from faculty, industry professionals, and students. The curriculum is designed to cover topics such as data warehousing, data mining, analytics, visualization, and big data technologies. The authors also discuss the different levels of the curriculum, which are tailored for undergraduate, master's, and MBA students. The paper concludes by highlighting the benefits of the model curriculum, including better preparedness for the workforce and increased competitiveness of the educational program, and the need for ongoing evaluation and updating to keep pace with changes in the field. In [5], Manavalan and Jayakrishna provided a review of the growing importance of sustainability in supply chain management and the role that IoT can play in achieving sustainable supply chain management. They reviewed the literature on the application of IoT in the supply chain, focusing on areas such as logistics, inventory management, quality control, and waste reduction. The authors also discussed the challenges associated with implementing IoT in the supply chain, such as data security and privacy, interoperability, and standardization.
In [6], Sahay et al. studied the significance of real-time BI for helping organizations gain better visibility into their supply chain operations, identify potential problems or inefficiencies, and make informed decisions to improve their overall performance. They explored the different components of real-time BI, including data integration, data warehousing, data mining, and reporting, then, emphasized the importance of integrating data from various sources in real time to ensure that decision-makers have access to the most up-to-date information. In [7], Hitt et al. explored the application of resource-based theory in operations management research. The authors begin by providing an overview of resource-based theory and its key concepts, such as resources, capabilities, and competitive advantage. They then reviewed the literature on the application of resource-based theory in operations management research, focusing on areas such as strategic sourcing, supply chain management, and operations strategy. They also discussed the challenges associated with applying resource-based theory in operations management research, such as the difficulty in measuring and identifying resources and capabilities. In [8], Maccarthy and Liu addressed the gap in scheduling research by reviewing optimization and heuristic methods in production scheduling. The authors discussed the importance of production scheduling in manufacturing and the challenges associated with scheduling in a dynamic and uncertain environment. They then reviewed the literature on optimization and heuristic methods in production scheduling, including mathematical programming, simulation, and heuristic algorithms. The authors provided a detailed description of each method, along with its advantages and limitations, and compared them in terms of their performance, complexity, and applicability to different scheduling problems. In [9], Brandenburg et al. provided a review of quantitative models for sustainable supply chain management (SSCM) and explored the developments and challenges associated with achieving sustainability in supply chain management. This involved reviewing the literature on quantitative models for SSCM, including life cycle assessment (LCA), multi-criteria decision-making (MCDM), and mathematical programming. The authors provide a detailed description of each method, along with its advantages and limitations. They also compare the methods in terms of their performance, complexity, and applicability to different SSCM problems.

In [10], Bonilla et al. examined the implications of Industry 4.0 for sustainability and presents a scenario-based analysis of the impacts and challenges of this emerging technology. They discussed the concept of Industry 4.0 and its potential to transform manufacturing using advanced technologies such as the Internet of Things (IoT), artificial intelligence (AI), and robotics. They then explored the sustainability implications of Industry 4.0, including its potential to reduce resource consumption, increase energy efficiency, and improve environmental performance. They used a qualitative method to develop the scenarios and analyze their implications for sustainability, considering economic, environmental, and social dimensions. In [11], Brax and Jonsson presented a comparative case study of two manufacturers that have developed integrated solution offerings for remote diagnostics they studied the importance of remote diagnostics in manufacturing and the potential benefits of integrating it with other offerings such as maintenance and repair services. The first case was a large manufacturer of construction

Doi: https://doi.org/10.54216/AJBOR.050104
Received: July 11, 2021 Accepted: September 29, 2021

equipment, which has developed a solution offering that integrates remote diagnostics with maintenance and repair services, while the second case is a small manufacturer of industrial equipment, which has developed a solution offering that integrates remote diagnostics with data analysis and decision support services.

3. Methodology

This section describes the research design of our study, data collection methods, the sampling strategy, data sources, and data analysis procedures, and justifies the choice of these methods.
The methodology of the study was informed by a real-world dataset collected from a company that makes televisions. An effort has been undertaken to discover a reliable model for foreseeing consumer demand. The study's secondary objective was to investigate the impact of manufacturing on predictive accuracy. The extent of this impact will be studied by looking at the costs of manufacturing at various levels. The proposed ML models are going to be evaluated in both low and high-manufacturing expense scenarios. When manufacturing costs are varied, it will be possible to see how ML models behave with regard to demand prediction. Detailed descriptions of each of the processes in the proposed technique are provided below.

The initial stage involved choosing which databases to use. The ISI Web of Science (WoS) database was chosen as the final step in the process, after the review of relevant literature. In fact, WoS is often regarded as the most important database in the study of economics and society. WoS is equivalent in size to Scopus, but its material is presented in a standardized format and involves minimal to no data cleansing. To make sure we didn't miss any relevant sources in the course of document extraction, we supplemented our automated search with some manual work on Google Scholar (GS) by keeping an eye on the papers that were cited in other high-quality journals. Publications were chosen according to their potential usefulness in addressing the research questions. Thus, it was decided to look into publications that regularly publish articles on AI, environmentally friendly growth, and technological advancement.

Features cited as necessary for a BI platform in a manufacturing setting are related to the BI tools that have been selected and analyzed in light of research conducted online (a literature study). There were a total of 10 people involved in the evaluation process (5 industrial participants and 5 IT specialists). The task of forming the team and supplying us with the final findings fell on the shoulders of a representative from the business community. After two rounds of evaluation, they gave us their final verdict on each component. We didn't meddle with the grading procedure in order to keep the results objective. As a final step, the family met with the accountable industrial participant to share their thoughts and receive feedback. As a result, Table 1 provides a comparison of the necessary tools and the prerequisites. The scale that follows has been used as the categorization factor for the comparative evaluation of the evaluated methods.

Table 1: Comparative Summary of BI Tools and their Features and Family.

Features	**Jaspersoft BI**	**Necto**	**Palo BI Suite**	**Microsoft Power BI**	**Pentaho BI Suite**	**SAP Business**	**QlikView**	**Spago BI**	**Tableau Public**	**Family**
Architecture	4	3	4	2	5	5	4	5	4	D
Attractiveness	4	4	3	4	4	3	5	5	4	C
Connection to the Database	5	4	4	2	4	2	5	5	3	A
Customization of the Interface	4	3	0	5	5	4	5	5	5	F
Dashboards	1	3	1	4	4	2	4	5	4	B
Data Mining	1	4	1	2	3	2	2	4	1	B
Display of KPIs	1	3	1	3	5	4	4	4	4	A

Doi: https://doi.org/10.54216/AJBOR.050104
Received: July 11, 2021 Accepted: September 29, 2021

Documentation	4	4	4	3	2	2	2	2	3	F
Ease of Use	4	3	4	2	4	4	4	4	5	F
ETL	4	4	5	5	5	2	3	4	1	E
Export	5	4	2	4	5	2	2	5	4	C
Integration of Dimensional Model	1	1	1	2	1	5	2	4	1	E
Interactive Visualization of Data	5	3	4	4	5	5	5	4	4	C
Navigation Features	5	4	4	5	4	4	1	2	4	C
OLAP Ad hoc Queries	1	5	5	2	5	5	3	5	4	B
Online Help	4	3	2	3	3	5	4	3	4	F
Open-source	5	4	5	5	5	2	1	5	5	D
Performance	4	5	3	4	4	2	3	4	4	D
Pervasive	5	3	5	2	5	4	1	5	4	A
Plug-ins	3	1	0	4	5	3	0	0	3	D
Real-time	5	2	4	2	5	4	1	5	1	A
Support for Mobile Devices	4	5	1	5	0	2	5	5	3	C
User Profile	5	3	4	3	5	2	1	4	0	D

0= unknown; 1=absent; 2=insufficient; 3=sufficient; 4= good, 5=excellent

A= Must Have, B=Technologies, C=End-User, D=Other Important, E=Data Processing, F=Administrator

Doi: https://doi.org/10.54216/AJBOR.050104
Received: July 11, 2021 Accepted: September 29, 2021

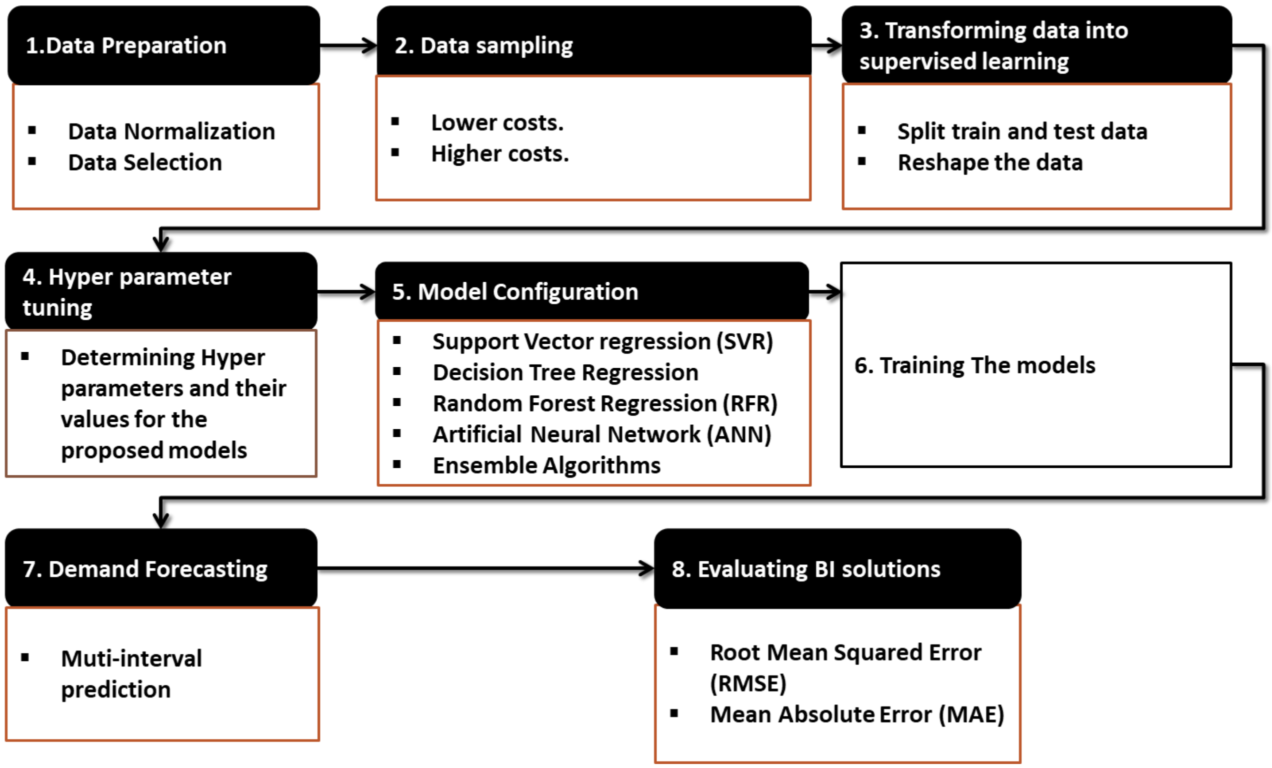

Figure 1. Illustration of the methodology of our PI pipeline for comparing different solutions in our comparative study.

As a result, each instrument was given a score based on each criterion. The rating shows how satisfied and compliant users are with the tool in relation to the analysed attribute. The evaluation relied on users' experiences and opinions. However, the needs were organised into categories based on how similar they were to one another following a thorough examination of each tool's features. All the criteria for a successful BI platform in the healthcare industry were divided into six categories and assigned weights accordingly. It is important to keep in mind that the contributors of this paper were part of a collaborative group of industry professionals and information technology experts. As a result, the authors of this study conducted a critical examination and evaluation of the viewpoints expressed by a number of experts whose work either directly or indirectly involves the use of BI tools. First, we selected the set of requirements that are so fundamental that they cannot be waived under any circumstances. The needs of the administrator building the BI platform were then separated into their own group. Given this demographic's relatively minor role within the manufacturing system, they were allocated 7%. Perhaps only the tool's administrator, the coder, will find any use in it. The set also included the subset whose members have BI platform user benefits. The percentage allotted to this category is 24-27%. The satisfaction of the final consumer is given a higher weight. If this doesn't work, implementing the platform can fail. As a result of their emphasis on research and analysis, the tools that make up the 30% most-associated category are the tools' underlying technologies. IT and medical professionals have no use for a BI platform that lacks essential functionality like OLAP technology and dashboards. Around twenty-five percent of the budget was allotted to other crucial aspects. Last, but not least, there is a 19% association between this group and data processing. All of the features in this category would improve the tool if implemented, but they won't have much of an impact on how well the BI platform is built. If the tool, for instance, could contain ETL techniques, it would be quite useful in the ETL process. But various tools can be used to carry out the ETL.

A study was developed using a real-market dataset from a television manufacturer in order to address the research concerns. To better estimate future demand, numerous models have been tested. The impact of manufacturing on the accuracy of the forecast was another goal of the research. Costs associated with manufacturing will be studied to learn more about this correlation. When manufacturing expenses are low and high, the proposed ML models will be compared for performance. This will allow for an examination of how changes in the manufacturing budget affect

Doi: https://doi.org/10.54216/AJBOR.050104
Received: July 11, 2021 Accepted: September 29, 2021

the efficacy of ML models used for demand forecasting. The proposed methodology is depicted in Fig. 1, and its individual steps will be detailed in greater depth below.

Prior to being employed in an ML analysis, time series data needs to undergo preliminary processing. Preparing data for use in predicting computations necessitates a number of steps, including examination of missing values and normalisation of the data. Analyzing whether the data is steady or not is also helpful because the information that changes over time might compromise the reliability of predictions. A set of input factors will be chosen for use in demand projections after missing value and stationary analysis have been performed. The data will then be subjected to a data normalisation process before being analysed further. In models for prediction, one of the most crucial tasks is choosing the independent variables that will be used for predicting the variables that are dependent. For example, if there is a strong correlation between the input factors or if some of the variables have low predictive power, this task may become quite challenging. Selecting appropriate input factors not only improves the model's capacity to predict but also shortens the time required for calculations by reducing the number of data points to be analysed. Big data and a large number of variables are commonplace in Neural Network (NN) models. The growing demand for NN models means that reliable methods for choosing input variables are more important than ever. As a result, the selection of variables has evolved into a pivotal stage in ML processes.

4. Results

The Augmented Dickey-Fuller (ADF) test is a statistical test used to determine if a time series data has a unit root, which is an indication of non-stationarity. In business intelligence, the ADF test can be used to analyze and model economic and financial time series data. The ADF test works by regressing the time series data on its lagged values and testing the null hypothesis that the data has a unit root (i.e., non-stationary). If the p-value of the test is less than a pre-specified level of significance, the null hypothesis is rejected, and the time series is considered stationary.

Table 2: The summary results of stationary ADF test.

ADF Statistic	***p*-value**	**Critical Value 1%**	**Critical Value 5%**	**Critical Value 10%**
− 3.433	0.034205	− 2.863	− 2.567	− 2.567

Table 3: The Iteration and the solutions of stepwise prediction

Iteration	**Included Variable**	***P* value**
1	Point of Sales (POS) Data	0.00002
2	Consumer Price Index (CPI)	0.00000
3	Sales ($)	0.00003
4	Manufacturing Expenses (Internet)	0.00007
5	Unit Price ($)	0.00010
6	Manufacturing Expenses (Radio)	0.00009
7	Manufacturing Expenses (TV)	0.00000
8	Manufacturing Expenses (SMS)	0.00014
9	Consumer Confidence Index (CCI)	0.00006
10	Steps ended since there are no variables with p values < 0.05	0.00006

Selecting variables is the following procedure in preparing information for predicting demand. The goal of using stepwise prediction is to determine which variables most strongly influence the dependent variable. In stepwise regression, eight of the sixteen variables that are independent are chosen for use in predicting demand. Table 3

Doi: https://doi.org/10.54216/AJBOR.050104
Received: July 11, 2021 Accepted: September 29, 2021

displays the procedures and outcomes of stepwise prediction. Table 4 shows the descriptive statistics of manufacturing data.

Table 4: Comparison of summary statistics of different variables in our data.

	Demand	**SALES ($)**	**(CPI**	**POS Data**	**Internet**	**Unit Price ($)**	**TV**	**SMS**	**CCI**
Number of observations	2615	2622	261307	2619	2616	2623	2620	2621	2619
Mean	5023	1641513	10268.00	4524	3086	365	3.325	70	103
Std. Deviation	2686	941670.3	148	2613	1528	34	126	15	11
Minimum	1613	462711.6	10140	1510	2	285	1072	43	100
Maximum	18571	5960226	10659	16490	6356	405	1483	100	110

The purpose of this research is to determine how manufacturing influences the accuracy of demand forecasting using ML methods. In order to clarify this impact, the collected data must be split into two groups: those with low and those with high overall manufacturing expenditures. Total manufacturing costs are determined by adding together the costs of each individual form of manufacturing for each day. The information is then ranked by rising overall manufacturing costs.

Total manufacturing expenditures were used to divide the data into four equal groups, or quartiles. We utilised the top and bottom quartiles to indicate days with high and low costs, correspondingly. A t-Test was performed to determine if there was a statistically significant difference between the low- and high-expenses groups. Before running the t-Test, we used the F-test to determine whether or not the two groups had similar variances. Table 4 displays the results of an F-test, which shows that the variances of the groups under consideration are not equal. It is now possible to do two-sample t-Tests with uneven variations. Variations between the low-manufacturing and high-manufacturing groups are statistically noteworthy according to t-Tests (see Table 6).

Table 5: The results of the F-test on Two-Sample Variations

	Mean	Variance	# Observations	F	P value one-tail	F Critical one-tail
Low market Expenses Group (Q1)	2,416,412,801	388,516,802	648	1,333,834,057	0,000,121,901	1,137,661,401
High market expenses Group (Q3)	608,557,085	2,831,817,534	657			

Table 6. The results of the Two-Sample T-test with the assumption of uneven std.

t Statistic	**P value (one-tail)**	**t Critical one-tail**	**P value (two-tail)**	**t Critical two-tail**
− 120,3,403,99	< 0.05	1,538,037,687	< 0.05	1,955,841,799

Predictions models of BI are evaluated on manufacturing data using root-mean-squared error and mean-absolute error. For calculating RMSE and MAPE, we use the optimal set of hyperparameters for each model. Furthermore, the MSE, as well as the MAPE metrics for the low and high manufacturing expenses groups, were presented independently in order to ascertain the impact of manufacturing on the efficacy of the models in predicting the market. The values for MSE and MAPE may be displayed in Table 7.

Doi: https://doi.org/10.54216/AJBOR.050104
Received: July 11, 2021 Accepted: September 29, 2021

Table 7: Comparative Results of ML solutions for BI-based pipeline for sustainable growth.

	Low-level market		**Low-level market**	
Method	**MSE**	**MAPE**	**MSE**	**MAPE**
Ridge regression	14510.91±13.28	7962.21±8.18	9322.65±7.75	7246.21±13.96
Decision tree	14113.19±6.59	8801.58±14.04	10260.25±12.73	7764.27±11.35
Random forest	14021.41±13.08	8126.45±13.6	10205.67±13.62	7091.67±12.84
Bayesian Regression	15025.37±14.56	7719.04±9.89	9526.6±7.67	7365.91±11.92
Voting Regressor	12888.95±7.64	8543.77±12.01	10177.75±14	7159.18±8.8
GradientBoosting Regressor	14913.9±13.68	7990.05±13.65	9368.76±14.61	7137.91±7.96
LGBMRegressor	13946.14±6.86	9446.38±13.06	9449.38±9.31	7197.6±9.41
Support vector	14191.1±12.2	9235.49±10.23	10745.44±6.97	7049.41±14.09
XGBoost	10957.79±8.01	7389.65±8.79	9714.6±11.5	7433.1±14.8
NN	13050.77±11.05	8559.01±10.46	9834.23±7.53	7350.77±11.12

5. Discussions

Using a set of data including manufacturing expenditures and sales, this research projected demand using ML approaches and identified the model that provided the most accurate demand forecast. The impact of manufacturing costs on the precision of demand forecasts is also investigated. Five ML methods have been employed to create demand estimates under varying levels of manufacturing spending. Since algorithms based on machine learning have been demonstrated to outperform conventional statistical approaches in time series forecasting of demand, they have been selected for use in this endeavor. In sum, the results validated the feasibility of using ML methods for demand forecasting. Compared to other algorithmic approaches, XGBoost, produce the best predictive results; this is particularly so for forecasting time series. This result agrees with others that have used XGBoost to predict time series. The maximum levels of accuracy achieved in this study utilizing XGBoost for projections of demand are in line with those achieved in previous studies. The results of this research also demonstrate that modifying the data format can enhance the predictive power of ML methods. More in-depth input data was found to improve forecasting of demand effectiveness. Demand accuracy for all ML models drastically increases when manufacturing expenditure is large. This result hints that ML approaches model the data better and produce more precise forecasts when manufacturing expenditures rise. This result agrees with those of other prior studies as well [6-13].

This research adds to the field of manufacturing by exploring ways to quantify the impact of manufacturing and media costs on demand using ML methods. These costs make up a sizeable portion of total manufacturing budgets. Thus, the study's application of ML techniques will aid with interpreting information in manufacturing, deepen our awareness of expanding potential markets, and lead to better decisions regarding manufacturing. It demonstrates the possibility of improved forecasting, which in turn increases the longevity of businesses. Efficient demand forecast by ML has the potential to improve sustainability in the areas of cost savings, decrease in emissions of carbon dioxide, reduced energy consumption, and time economies. The results of the suggested model help the manufacturing industry determine the optimal conditions for using ML demand forecasting techniques. The study found that all ML models' prediction accuracy increased significantly under conditions of high manufacturing costs. This result shows that as manufacturing costs rise, ML methods get a deeper understanding of the underlying data structure and become capable of producing more reliable forecasts. Our research assessed the efficacy of ML techniques in both high- and low-spending manufacturing environments. The results showed that when manufacturing budgets were larger, prediction performance improved across the board for the ML methods tested.

Doi: https://doi.org/10.54216/AJBOR.050104
Received: July 11, 2021 Accepted: September 29, 2021

Policymakers and managers will benefit from this study's findings. This research can help the manufacturing industry allocate its budget more effectively. Since manufacturing is a costly promotional activity, businesses aim to both minimise manufacturing expenditures and maximise manufacturing's impact on revenue and consumer demand. Study findings will also help most marketers make smart choices about how much to spend on manufacturing and how effectively different strategies are working to boost sales. The study's findings, then, have relevance for gauging manufacturing's ROI and its impact on demand. This study suggests that businesses should increase their manufacturing budgets if they accurately predict demand and believe that external forces are responsible for this prediction. Increased manufacturing expenditures not only boost sales, but also provide more reliable outcomes and useful guidance for future planning thanks to machine methods for learning. Manufacturing budgets may be increased if a company has access to significant amounts of data that can be evaluated using ML techniques. The amount spent on manufacturing can be kept low and statistical methods utilised for demand forecasting if the company does not have access to adequate funding and technical equipment.

6. Conclusion

This research provided valuable insight into the effectiveness of BI and OR in achieving sustainable growth in both manufacturing and service industries. We compare the two approaches, highlighting their strengths and weaknesses, and identify the conditions under which each approach is most effective. We also emphasized the importance of sustainability in business operations, highlighting the potential benefits of using BI and OR to reduce waste, increase efficiency, and improve the bottom line. We provide several case studies to demonstrate the effectiveness of BI and OR in achieving sustainability goals in different industries, highlighting the need for organizations to align their sustainability goals with their overall business objectives. We emphasize the need for organizations to embrace both BI and OR in their decision-making processes, as each approach has its unique strengths and can be used in combination to achieve optimal results. The paper provides a solid foundation for future research in this area, and its insights are relevant to organizations in both manufacturing and service industries looking to achieve sustainable growth.

References

[1]. Lopes de Sousa Jabbour, A. B., Jabbour, C. J. C., Godinho Filho, M., & Roubaud, D. (2018). Industry 4.0 and the circular economy: a proposed research agenda and original roadmap for sustainable operations. *Annals of Operations Research*, *270*, 273-286.

[2]. Kumar, A., Sah, B., Singh, A. R., Deng, Y., He, X., Kumar, P., & Bansal, R. C. (2017). A review of multi criteria decision making (MCDM) towards sustainable renewable energy development. *Renewable and Sustainable Energy Reviews*, *69*, 596-609.

[3]. Liu, Y., & Xu, X. (2017). Industry 4.0 and cloud manufacturing: A comparative analysis. *Journal of Manufacturing Science and Engineering*, *139*(3).

[4]. Gupta, B., Goul, M., & Dinter, B. (2015). Business intelligence and big data in higher education: Status of a multi-year model curriculum development effort for business school undergraduates, MS graduates, and MBAs. *Communications of the Association for Information Systems*, *36*(1), 23.

[5]. Manavalan, E., & Jayakrishna, K. (2019). A review of Internet of Things (IoT) embedded sustainable supply chain for industry 4.0 requirements. *Computers & Industrial Engineering*, *127*, 925-953.

[6]. Sahay, B. S., & Ranjan, J. (2008). Real time business intelligence in supply chain analytics. *Information Management & Computer Security*.

[7]. Hitt, M. A., Xu, K., & Carnes, C. M. (2016). Resource based theory in operations management research. *Journal of operations management*, *41*, 77-94.

[8]. Maccarthy, B. L., & Liu, J. (1993). Addressing the gap in scheduling research: a review of optimization and heuristic methods in production scheduling. *The International Journal of Production Research*, *31*(1), 59-79.

[9]. Brandenburg, M., Govindan, K., Sarkis, J., & Seuring, S. (2014). Quantitative models for sustainable supply chain management: Developments and directions. *European journal of operational research*, *233*(2), 299-312.

Doi: https://doi.org/10.54216/AJBOR.050104
Received: July 11, 2021 Accepted: September 29, 2021

[10]. Bonilla, S. H., Silva, H. R., Terra da Silva, M., Franco Gonçalves, R., & Sacomano, J. B. (2018). Industry 4.0 and sustainability implications: A scenario-based analysis of the impacts and challenges. *Sustainability*, *10*(10), 3740.
[11]. Brax, S. A., & Jonsson, K. (2009). Developing integrated solution offerings for remote diagnostics: A comparative case study of two manufacturers. *International journal of operations & production management*, *29*(5), 539-560.
[12]. Jahangirian, M., Eldabi, T., Naseer, A., Stergioulas, L. K., & Young, T. (2010). Simulation in manufacturing and business: A review. *European journal of operational research*, *203*(1), 1-13.
[13]. Bazmi, A. A., & Zahedi, G. (2011). Sustainable energy systems: Role of optimization modeling techniques in power generation and supply—A review. *Renewable and sustainable energy reviews*, *15*(8), 3480-3500.
[14]. Trieu, V. H. (2017). Getting value from Business Intelligence systems: A review and research agenda. *Decision Support Systems*, *93*, 111-124.
[15]. Aksin, Z., Armony, M., & Mehrotra, V. (2007). The modern call center: A multi-disciplinary perspective on operations management research. *Production and operations management*, *16*(6), 665-688.
[16]. D'Amato, D., Droste, N., Allen, B., Kettunen, M., Lähtinen, K., Korhonen, J., ... & Toppinen, A. (2017). Green, circular, bio economy: A comparative analysis of sustainability avenues. *Journal of cleaner production*, *168*, 716-734.
[17]. Ray, S., Boyaci, T., & Aras, N. (2005). Optimal prices and trade-in rebates for durable, remanufacturable products. *Manufacturing & Service Operations Management*, *7*(3), 208-228.

Doi: https://doi.org/10.54216/AJBOR.050104
Received: July 11, 2021 Accepted: September 29, 2021