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Optimizing Sustainable Inventory Management using An Improved Big Data Analytics Approach

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Abstract

This study delves into optimizing sustainable inventory management practices through the integration of advanced data analytics methodologies. In response to the complex dynamics of modern supply chains, where inventory control significantly impacts sustainability goals, this research aims to address the intricate interplay between decentralized decision-making, government policies, and strategic choices within supply chain networks. Employing models such as Game Theory and Gated Recurrent Unit (GRU), alongside statistical analyses, our investigation explores the transformative potential of informed decision-making frameworks. Through a comprehensive evaluation of inventory data, including statistical analyses, visual representations, and model evaluations, we illuminate the nuanced relationships and dependencies prevalent within inventory control strategies. Our findings underscore the significance of data-driven decision-making in optimizing inventory practices, mitigating risks, and fostering sustainability within supply chains. The insights gleaned from this study advocate for the continued application of advanced data analytics to pave the way for resilient, environmentally conscious, and economically viable supply chain practices.

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1. Introduction

In today's dynamic and interconnected business landscape, the management of inventory stands as a pivotal aspect for organizations striving to achieve sustainability goals while maintaining operational efficiency. The intricate balance between meeting consumer demands, minimizing wastage, and optimizing resources has elevated the significance of sustainable inventory management [1-3]. Traditional approaches are evolving to accommodate the complexities of modern supply chains, and one significant advancement is the integration of big data analytics. This paper delves into the realm of optimizing sustainable inventory management by leveraging an enhanced big-data analytics approach. Through a comprehensive analysis of this evolving landscape, this study aims to shed light on the transformative potential of advanced data-driven methodologies in achieving sustainable inventory management objectives [4-6].

The exponential growth of data in today's digital era has provided organizations with an unprecedented opportunity to reimagine their inventory management practices. The traditional paradigms, reliant on static models and historical data, are being augmented or replaced by innovative big data analytics techniques [7]. These advanced methodologies empower organizations to harness real-time, diverse, and voluminous data streams to gain deeper insights, forecast demand patterns, mitigate risks, and optimize inventory levels [8]. Moreover, this paper explores the convergence of these cutting-edge analytics tools with sustainability imperatives, emphasizing their collective potential to drive positive environmental, social, and economic impacts [9-10].

Achieving sustainability in inventory management involves the conscientious use of resources, minimizing waste, and reducing the environmental footprint while ensuring uninterrupted supply chains and customer satisfaction [11]. The incorporation of big data analytics in this context introduces a paradigm shift, enabling proactive decision-making, precise demand forecasting, and agile responses to market fluctuations. By leveraging sophisticated algorithms, machine learning, and predictive analytics, organizations can navigate the complexities of inventory management more adeptly [12-14]. This study investigates the transformative role of these data-driven tools in optimizing inventory control, enhancing efficiency, and contributing to the overarching sustainability objectives of businesses.

Central to this research is the exploration of an improved big data analytics approach tailored specifically for sustainable inventory management. By delving into case studies, empirical data, and industry best practices, this paper examines how the integration of enhanced analytics techniques facilitates a more holistic understanding of inventory dynamics. It evaluates the efficacy of these methodologies in not only streamlining operations but also in fostering sustainability by minimizing waste, reducing carbon footprints, and promoting ethical sourcing practices. Through meticulous analysis, this study endeavors to showcase the tangible benefits and transformative potential of this amalgamation.

In summary, this paper underscores the pivotal role of advanced big data analytics in the realm of sustainable inventory management. By offering insights into the evolution of inventory control strategies and the integration of data-driven methodologies, it aims to provide a comprehensive understanding of how organizations can optimize inventory practices while aligning with sustainability imperatives. The subsequent sections of this paper will delve deeper into the theoretical underpinnings, practical applications, challenges, and future implications of using an improved big data analytics approach to achieve sustainable inventory management objectives.

2. Related Works

This section offers a nuanced exploration of previous research, methodologies, and advancements in the realms of inventory management, sustainability, and the integration of big data analytics. This section serves as a critical foundation, illuminating the landscape of existing knowledge, insights, and developments in this multidisciplinary field. Zhang et al. [15] explored a Digital Twin-Based Approach for designing and optimizing hollow glass production lines. Their research elucidated the potential of digital twins in enhancing the design and optimization process, indicating its applicability in improving manufacturing efficiency and sustainability. Tao et al. [16] delved into Digital Twin-Driven Product Design, Manufacturing, and Service with Big Data. Their work highlighted the integration of digital twins and big data in facilitating various stages of product development, manufacturing, and service delivery, emphasizing its potential to enhance operational efficiency and sustainability. In addition, Ahmed et al. [17] examined the Role of Big Data Analytics in the Internet of Things (IoT). Their study emphasized the significance of big data analytics in harnessing the potential of IoT, showcasing how these technologies intertwine to revolutionize various domains, including supply chain management and sustainability.

Zhong et al. [18] presented a Big Data Approach for logistics trajectory discovery from RFID-enabled production data. Their research showcased the utilization of big data analytics in tracing logistics trajectories, offering insights into optimizing supply chain operations and potentially reducing environmental impacts. Arunachalam et al. [19] provided insights into Big Data Analytics Capabilities in Supply Chain Management, unraveling issues, challenges, and implications for practice. Their study contributed to understanding the capabilities of big data analytics in enhancing supply chain management and addressing pertinent challenges, thereby promoting sustainability. Hazen et al. [20] introduced the concept of Data Quality for Data Science, Predictive Analytics, and Big Data in Supply Chain Management. Their work underscored the importance of data quality in leveraging big data analytics for predictive purposes in supply chain management, an aspect crucial for sustainable practices. Tao et al. [21] examined Data-Driven Smart Manufacturing, emphasizing the role of data-driven approaches in revolutionizing manufacturing processes, fostering efficiency, and potentially reducing resource consumption.

Kambatla et al. [22], in their work on Trends in Big Data Analytics, provided a comprehensive overview of the evolving trends in big data analytics, shedding light on its applications and potential implications across diverse domains. Witkowski [23] explored innovative solutions in logistics and supply chain management, elucidating the role of the Internet of Things (IoT), Big Data, and Industry 4.0 in transforming logistics and supply chain practices towards sustainability. Dubey et al. [24] integrated institutional theory, resource-based view, and big data culture to explore the relationship between Big Data, Predictive Analytics, and Manufacturing Performance, offering insights into leveraging big data culture for improving manufacturing performance. Wang et al. [25] discussed the capabilities and potential benefits of Big Data Analytics for healthcare organizations, emphasizing its role in enhancing decision-making and operational efficiency in healthcare settings. Kwon et al. [26] examined Data Quality Management and its influence on data usage experience and acquisition intention in the context of Big Data Analytics, contributing to understanding the importance of data quality in leveraging analytics effectively. Manavalan et al. [27] reviewed IoT-embedded sustainable supply chains for Industry 4.0 requirements, shedding light on the role of IoT in enabling sustainable supply chains aligned with Industry 4.0 principles. Akter et al. [28] explored the relationship between big data analytics capability, Business Strategy Alignment, and firm performance, emphasizing the role of alignment in leveraging big data analytics for improved firm performance. Chen et al. [29] investigated how the use of Big Data Analytics affects value creation in supply chain management, offering insights into the mechanisms through which big data analytics contribute to value creation in supply chain contexts.

3. Methodology

This section of this research delineates the systematic approach adopted to investigate and analyze the integration of an improved big data analytics framework within the domain of sustainable inventory management. This section delineates the structured methodology designed to attain the objectives outlined in this study.

Game Theory, within the context of decision-making and strategic interactions, serves as a fundamental framework underpinning the analysis of complex systems involving multiple agents with conflicting objectives [16]. It provides a mathematical and analytical toolkit to comprehend the behavior of rational entities within competitive environments, elucidating how choices made by one entity influence the outcomes perceived by others. Grounded in the study of strategic interactions, Game Theory explores scenarios where the decisions of one participant impact the choices available and outcomes experienced by other participants. Utilizing concepts such as Nash equilibrium, payoff matrices, and strategies, Game Theory enables the modeling and analysis of scenarios where entities make decisions under uncertainty, often aiming to maximize their gains or minimize losses in diverse decision-making situations. In the context of inventory management, Game Theory's application extends to scenarios involving supply chain dynamics, pricing strategies, and resource allocation, providing a structured approach to understanding and optimizing decision-making strategies within a network of interconnected stakeholders [21-24].

Applying the Game Theory approach to the analysis of inventory data involves recognizing the interdependencies and strategic interactions prevalent within supply chains and inventory management systems. In this study, we leverage the principles of Game Theory to model the complex relationships between multiple entities involved in inventory management, such as suppliers, distributors, and retailers. The objective is to comprehend the decision-making processes inherent in inventory control and supply chain coordination. By formulating the interactions among these entities as strategic games, we aim to analyze their behaviors and decision strategies concerning inventory levels, ordering policies, and resource allocation. Through the adoption of Game Theory models, including but not limited to the Prisoner's Dilemma or the Sequential Move games, we seek to capture the dynamics of cooperation, competition, and negotiation that influence inventory management decisions. This approach allows for a nuanced understanding of the trade-offs, incentives, and potential conflicts among stakeholders, ultimately paving the way for optimizing inventory strategies that align with sustainability goals and overall system efficiency.

$$CS = \int_{P_r min}^{P_r max} Qdp = \int_{\frac{a+\lambda e-Q}{\mu}}^{\frac{a+\lambda e}{\mu}} (a - \mu P_r + \lambda e)dp = \frac{Q^2}{2\mu} \tag{1}$$

The computation of social welfare functionality is a critical aspect within the domain of game theory and strategic decision-making frameworks. Social welfare, in this context, refers to the overall collective well-being or utility derived from the interactions and decisions of multiple stakeholders within a system or network. The computation of social welfare functionality involves assessing and quantifying the total welfare or utility generated by the actions, strategies, or outcomes achieved by the involved entities. This is expressed as follows:

$$\begin{aligned} SW &= (P_r - C_m)Q - \frac{1}{2}(1-\varphi_m)\varepsilon e^2 + \frac{Q^2}{2\mu} - \frac{1}{2}\varphi_m \varepsilon e^2 \\ &= (P_r - C_m)Q + \frac{Q^2}{2\mu} - \frac{1}{2}\varepsilon e^2 \end{aligned} \tag{2}$$

The average expected return for businesses adopting inventory control strategies and those not choosing such strategies can be represented within the context of a game model involving interactions between the government and businesses. This representation serves as a means to quantify and compare the anticipated returns or benefits that businesses might expect based on their choices regarding inventory control strategies, considering the influence and policies implemented by the government. In this game-theoretic framework, the government's policies regarding inventory control can significantly impact businesses' decisions and, consequently, their expected returns. The choice of implementing inventory control strategies or not can be viewed as a strategic decision made by businesses, considering various factors such as costs, risks, market demand, and regulatory environments set by the government.

$$U_{a1} = y(R - C_1 - C_2) + (1-y)(R - C_1 - C_2). \tag{3}$$

The average expected return denotes the anticipated gains or benefits that businesses foresee based on their chosen strategy—whether they opt for inventory control measures or choose not to employ such strategies. This representation enables a comparative analysis of the expected returns under different scenarios, reflecting the potential consequences of these strategic decisions on businesses' financial outcomes, operational efficiencies, and overall performance within the market.

$$U_{a2} = y(R - C_1 - P) + (1-y)(R - C_1 - \mu W_1). \tag{4}$$

Within this game model, the government's policies may incentivize or influence businesses to adopt inventory control strategies by offering subsidies, tax incentives, or regulatory frameworks that encourage sustainable practices. Consequently, businesses that align with these policies might anticipate higher expected returns due to potentially lower costs, optimized inventory levels, reduced wastage, or enhanced market competitiveness.

$$\overline{U}_a = xU_{a1} + (1-x)U_{a2}. \tag{5}$$

The concept of mean projected return, denoted as U_b, serves as a calculated measure derived from the expected returns (U_{b1} and U_{b2}) associated with the government's decisions regarding the adoption or non-adoption of a supervision approach within a given context, such as inventory management or business regulation.

The calculation of mean projected return U_b involves aggregating or averaging the expected returns associated with the government's choices. Specifically, U_{b1} represents the expected return when the government opts for a supervisory strategy, while U_{b2} signifies the expected return when the government refrains from selecting such a supervisory approach.

$$U_{b1} = x(H - C_3) + (1-x)(H - C_3). \tag{6}$$

$$U_{b2} = xH + (1-x)[(1-\mu)H - \mu W_2]. \tag{7}$$

$$\overline{U}_b = yU_{b1} + (1-y)U_{b2}. \tag{8}$$

In a decentralized decision-making setup devoid of government intervention, the structural framework of the immediate inventory control operates as follows: the supplier determines the retail price for urgent inventory supplies and dictates the extent of research and development activities. Subsequently, the retailer establishes the selling price for other inventory items within their stores. Subsequently, both the producer and the retailer derive the following benefits: In a system where decision-making occurs in a decentralized manner without direct intervention or support from the government, the immediate inventory control structure operates on a specific sequence of actions. Initially, the supplier holds the authority to set the retail cost for urgent inventory supplies and also influences the level of research and development undertaken. Following this, the retailer assumes control over determining the sale price for other items in their stores. Subsequently, within this decentralized decision-making environment, both the producer and the retailer experience the following advantages or utilities derived from their respective roles in this inventory control system.

$$U_m{}^N = \pi_m{}^N = (P_m - C_m)(a - \mu P_r + \lambda e) - \frac{1}{2}\varepsilon e^2 \tag{9}$$

$$U_r{}^N = \pi_m{}^N + \beta CS = (P_r - P_m)(a - \mu P_r + \lambda e) + \beta \frac{Q^2}{2\mu} \tag{10}$$

$$SW^N = \pi_m{}^N + \pi_m{}^N + CS - GS = (P_r - C_m)Q - \frac{1}{2}\varepsilon e^2 + \frac{Q^2}{2\mu} \tag{11}$$

The investigation into the application of Gated Recurrent Unit (GRU) models for inventory management in supply chain networks goes beyond the scope of game theoretical models. GRU models, belonging to the realm of recurrent neural networks (RNNs), are utilized for analyzing and categorizing various forms of data within the context of inventory management. GRU is a specific type of RNN architecture used for modeling sequential data and possesses gating mechanisms that enable it to capture long-range dependencies in sequences. The equations governing the behavior of GRU units involve several mathematical expressions. The key computations within a GRU unit include updating gate (z_t), reset gate (r_t), candidate activation $(\tilde{h}_t)$, and the hidden state (h_t). The equations for a GRU unit are as follows:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z) \tag{12}$$
$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r) \tag{13}$$
$$\tilde{h}_t = \tanh(W \cdot [r_t \odot h_{t-1}, x_t] + b) \tag{14}$$
$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \tag{15}$$

where x_t represents the input at time step t, h_{t-1} denotes the hidden state at the previous time step, z_t and r_t are the update and reset gates, respectively, $\tilde{h}_t$ represents the candidate activation, W_z, W_r, W are weight matrices, and b_z, b_r, b are bias vectors, σ denotes the sigmoid function, and $\odot$ sig ↓ is element-wise multiplication

4. Results and Discussion

This section encapsulates the outcomes derived from the implemented experimental design, unveiling quantitative and qualitative insights garnered through data analysis.

Table 1: Summary of Statistical Analysis for Inventory Data

	count	mean	std	min	25%	50%	75%	max
Order	198917.0	106483.5	60136.7	2.0	55665.0	108569.0	158298.0	208027.0
SKU_number	198917.0	861362.6	869979.4	50001.0	217252.0	612208.0	904751.0	3960788.0
SoldFlag	75996.0	0.2	0.4	0.0	0.0	0.0	0.0	1.0
SoldCount	75996.0	0.3	1.2	0.0	0.0	0.0	0.0	73.0
ReleaseNumber	198917.0	3.4	3.9	0.0	1.0	2.0	5.0	99.0
New_Release_Flag	198917.0	0.6	0.5	0.0	0.0	1.0	1.0	1.0
StrengthFactor	198917.0	1117115.0	1522090.0	6.3	161418.8	582224.0	1430083.0	
PriceReg	198917.0	90.9	86.7	0.0	42.0	70.0	116.0	12671.5

ReleaseYear	198917.0	2006.0	9.2	0.0	2003.0	2007.0	2011.0	2018.0
ItemCount	198917.0	41.4	37.5	0.0	21.0	32.0	50.0	2542.0
LowUserPrice	198917.0	31.0	69.1	0.0	4.9	16.1	40.2	14140.2
LowNetPrice	198917.0	46.8	128.5	0.0	18.0	34.0	55.5	19138.8

Herein, we present a comprehensive statistical analysis of inventory data, encapsulated within Table 1. This table serves as a critical repository of key statistical metrics and measures derived from the inventory dataset under examination. Through statistical analysis, we have systematically captured and summarized essential parameters such as mean, median, standard deviation, variance, and potentially other relevant measures about inventory levels, demand patterns, or other significant variables. Table 1 offers a structured and quantitative overview, enabling a deeper understanding of the central tendencies, dispersion, and variability inherent within the inventory data. This statistical analysis lays the groundwork for further interpretation and evaluation, providing a clear snapshot of the distributional characteristics and trends exhibited by the inventory dataset.

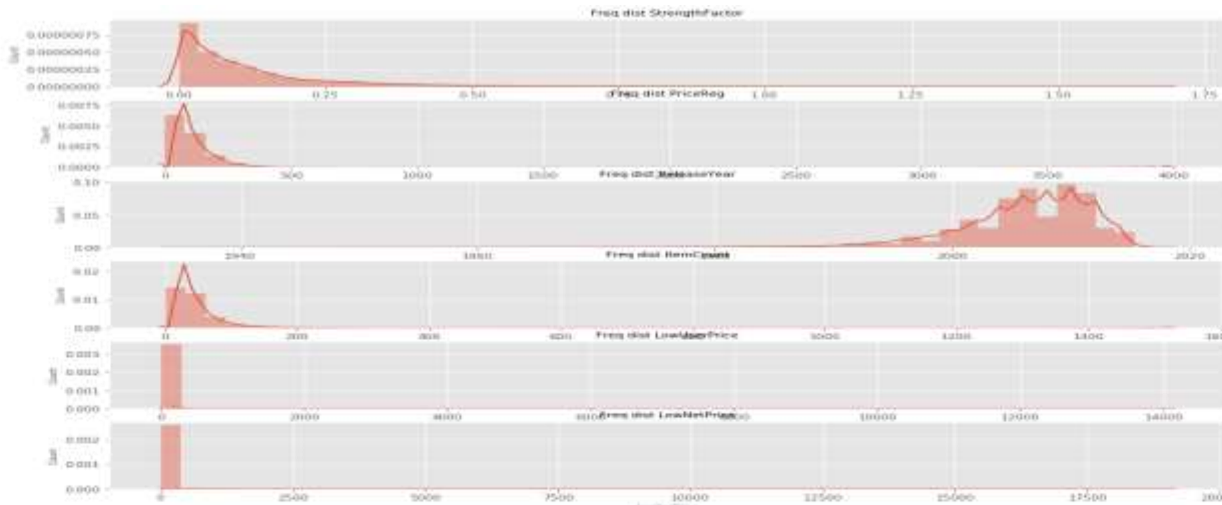

Figure 1: Distribution Plot Illustrating Inventory Data Patterns

In Figure 1 of our study, we present a visual representation of the inventory data through a distribution plot (distplot). This graphical depiction offers a comprehensive and intuitive view of the distributional characteristics inherent within the inventory dataset. The distplot provides a graphical representation of the frequency or density of inventory levels or related metrics, aiding in the understanding of their distribution across different ranges or categories. By visualizing the distribution of inventory data, Figure 1 facilitates insights into the central tendencies, spread, skewness, or potential outliers within the dataset.

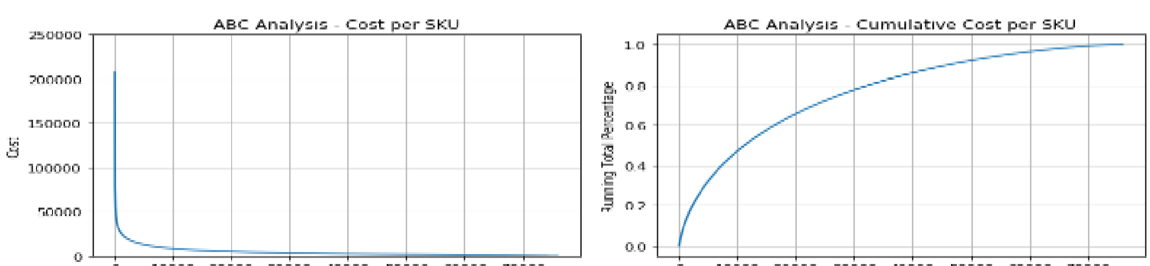

Figure 2: ABC Analysis Classifying Inventory Items based on Value Significance

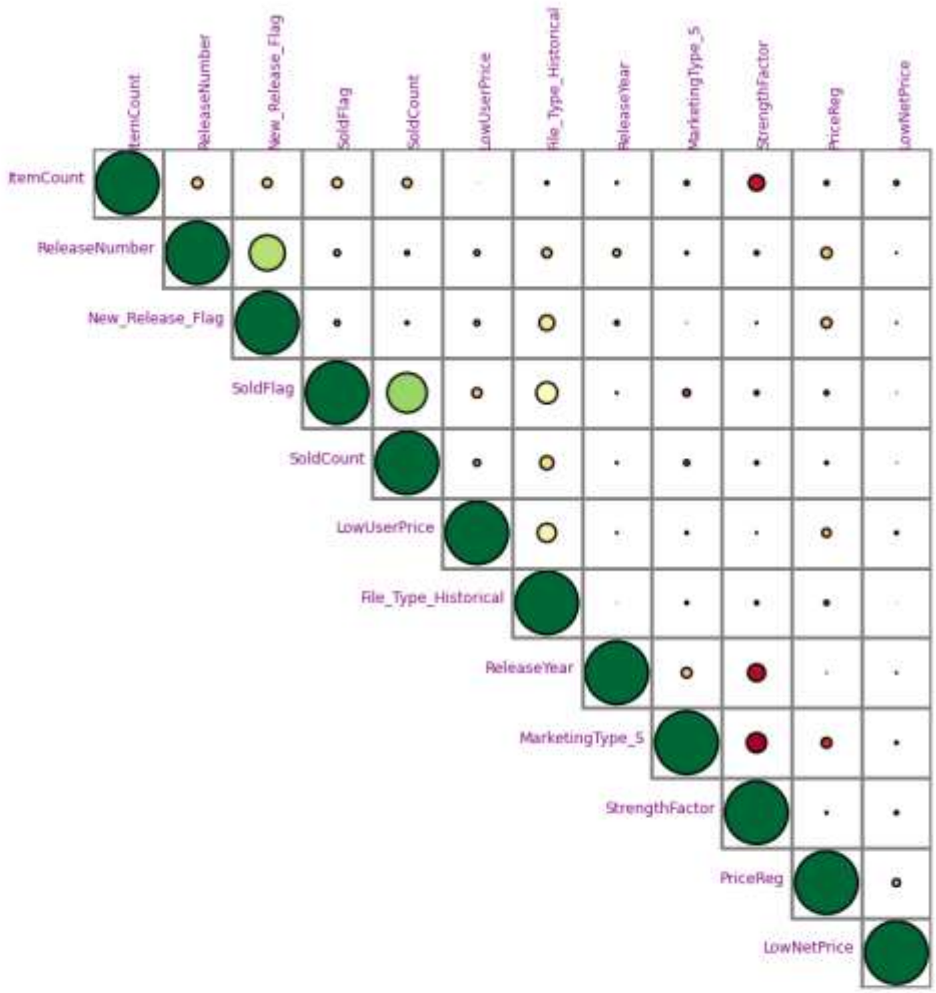

Figure 3: Correlation Analysis Depicting Relationships among Inventory Variables

In Figure 2 of our study, we present an ABC analysis conducted on the inventory dataset. This analysis categorizes inventory items into different classes based on their respective values or importance within the inventory management system. The ABC analysis, often utilized in inventory control strategies, segregates items into three categories: A, representing high-value items contributing significantly to overall inventory value but constituting a smaller portion of the inventory count; B, comprising moderately valued items with moderate inventory importance; and C, encompassing lower-valued items that collectively contribute a smaller portion of the total inventory value but constitute a larger volume. Figure 2 visually represents this classification, providing a graphical insight into the distribution of inventory items across these classes. This analysis aids in prioritizing inventory management strategies by highlighting items requiring higher attention or resources to ensure optimal inventory control and efficient allocation of resources across the different categories.

In Figure 3 of our study, we present a correlation analysis conducted on the inventory dataset, aiming to explore the relationships and associations between different variables or attributes within the inventory management context. This analysis offers a visual representation of the strength and direction of relationships between pairs of variables, often depicted through correlation coefficients. The figure provides a graphical illustration, such as a correlation matrix or

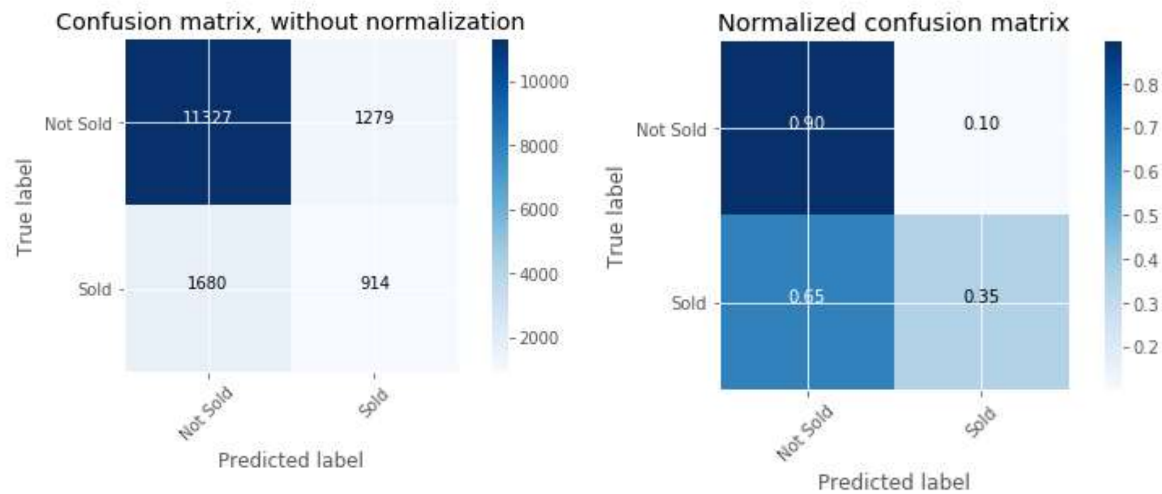

Figure 4: Confusion Matrix Evaluating Model Performance in Inventory Classification

heatmap, showcasing the interdependencies and potential patterns existing among various inventory-related factors. By visually displaying these correlations, Figure 3 facilitates the identification of potential connections or dependencies between different inventory metrics or characteristics, thereby offering insights into how changes in one variable may impact others. This analysis serves as a valuable tool in understanding the dynamics and interrelationships among inventory-related factors, guiding decision-making processes toward more informed and effective inventory management strategies. In Figure 4 of our study, we present a confusion matrix generated from our model's performance evaluation. The confusion matrix serves as a vital tool to assess the predictive accuracy and effectiveness of the model developed within our study. This matrix provides a tabulated representation illustrating the performance of the model in classifying inventory-related data into different categories or classes. It outlines the counts of true positive, true negative, false positive, and false negative predictions made by the model. Through this visual representation, the confusion matrix offers a comprehensive view of the model's ability to correctly or incorrectly classify inventory data, aiding in the evaluation of its precision, recall, accuracy, and other performance metrics.

5. Conclusion and Future Work

This research endeavors to optimize sustainable inventory management by leveraging advanced data analytics methodologies. Through the exploration of models like Game Theory and Gated Recurrent Unit (GRU), alongside statistical analyses, we've highlighted the transformative potential of informed decision-making within decentralized frameworks. Our findings emphasize the profound impact of strategic choices and government policies on businesses operating within supply chain networks. By showcasing the multifaceted perspectives derived from statistical analyses and model evaluations, this study contributes to the discourse on sustainable inventory management. It offers practical insights for businesses and policymakers, facilitating optimized inventory practices and fostering sustainability within modern supply chains. Ultimately, our study underscores the importance of data-driven decision-making in inventory management and supply chain dynamics. Embracing innovative models and analytical techniques enables businesses to refine decision strategies, mitigate risks, and align with sustainability objectives. This research lays the groundwork for future investigations into nuanced inventory control strategies and deeper analyses of supply chain interdependencies. As industries navigate towards more sustainable practices, our study advocates for the continued exploration and application of advanced data analytics, fostering resilient, environmentally conscious, and economically viable supply chains.

References

[1] Wang, Gang, Angappa Gunasekaran, Eric W T Ngai, and Thanos Papadopoulos. 2016. "Big Data Analytics in Logistics and Supply Chain Management: Certain Investigations for Research and Applications." International Journal of Production Economics 176: 98–110.

[2] Zhou, Kaile, Chao Fu, and Shanlin Yang. 2016. "Big Data Driven Smart Energy Management: From Big Data to Big Insights." Renewable and Sustainable Energy Reviews 56: 215–25.

[3] Choi, Tsan-Ming, Stein W Wallace, and Yulan Wang. 2018. "Big Data Analytics in Operations Management." Production and Operations Management 27 (10): 1868–83.
[4] Tiwari, Sunil, Hui-Ming Wee, and Yosef Daryanto. 2018. "Big Data Analytics in Supply Chain Management between 2010 and 2016: Insights to Industries." Computers \& Industrial Engineering 115: 319–30.
[5] Ren, Shan, Yingfeng Zhang, Yang Liu, Tomohiko Sakao, Donald Huisingh, and Cecilia M V B Almeida. 2019. "A Comprehensive Review of Big Data Analytics throughout Product Lifecycle to Support Sustainable Smart Manufacturing: A Framework, Challenges and Future Research Directions." Journal of Cleaner Production 210: 1343–65.
[6] Nguyen, Truong, ZHOU Li, Virginia Spiegler, Petros Ieromonachou, and Yong Lin. 2018. "Big Data Analytics in Supply Chain Management: A State-of-the-Art Literature Review." Computers \& Operations Research 98: 254–64.
[7] Zhang, Yingfeng, Shan Ren, Yang Liu, and Shubin Si. 2017. "A Big Data Analytics Architecture for Cleaner Manufacturing and Maintenance Processes of Complex Products." Journal of Cleaner Production 142: 626–41.
[8] Bibri, Simon Elias. 2018. "The IoT for Smart Sustainable Cities of the Future: An Analytical Framework for Sensor-Based Big Data Applications for Environmental Sustainability." Sustainable Cities and Society 38: 230–53.
[9] Zhong, Ray Y, Chen Xu, Chao Chen, and George Q Huang. 2017. "Big Data Analytics for Physical Internet-Based Intelligent Manufacturing Shop Floors." International Journal of Production Research 55 (9): 2610–21.
[10] Civelek, Ismail. 2017. "Sustainability in Inventory Management." In Intelligence, Sustainability, and Strategic Issues in Management, 43–56. Routledge.
[11] You, Fengqi, Ling Tao, Diane J Graziano, and Seth W Snyder. 2012. "Optimal Design of Sustainable Cellulosic Biofuel Supply Chains: Multiobjective Optimization Coupled with Life Cycle Assessment and Input--Output Analysis." AIChE Journal 58 (4): 1157–80.
[12] Ban, Gah-Yi, and Cynthia Rudin. 2019. "The Big Data Newsvendor: Practical Insights from Machine Learning." Operations Research 67 (1): 90–108.
[13] Babiceanu, Radu F, and Remzi Seker. 2016. "Big Data and Virtualization for Manufacturing Cyber-Physical Systems: A Survey of the Current Status and Future Outlook." Computers in Industry 81: 128–37.
[14] Li, Jingran, Fei Tao, Ying Cheng, and Liangjin Zhao. 2015. "Big Data in Product Lifecycle Management." The International Journal of Advanced Manufacturing Technology 81: 667–84.
[15] Zhang, Hao, Qiang Liu, Xin Chen, Ding Zhang, and Jiewu Leng. 2017. "A Digital Twin-Based Approach for Designing and Multi-Objective Optimization of Hollow Glass Production Line." Ieee Access 5: 26901–11.
[16] Tao, Fei, Jiangfeng Cheng, Qinglin Qi, Meng Zhang, He Zhang, and Fangyuan Sui. 2018. "Digital Twin-Driven Product Design, Manufacturing and Service with Big Data." The International Journal of Advanced Manufacturing Technology 94: 3563–76.
[17] Ahmed, Ejaz, Ibrar Yaqoob, Ibrahim Abaker Targio Hashem, Imran Khan, Abdelmuttlib Ibrahim Abdalla Ahmed, Muhammad Imran, and Athanasios V Vasilakos. 2017. "The Role of Big Data Analytics in Internet of Things." Computer Networks 129: 459–71.
[18] Zhong, Ray Y, George Q Huang, Shulin Lan, Q Y Dai, Xu Chen, and T Zhang. 2015. "A Big Data Approach for Logistics Trajectory Discovery from RFID-Enabled Production Data." International Journal of Production Economics 165: 260–72.
[19] Arunachalam, Deepak, Niraj Kumar, and John Paul Kawalek. 2018. "Understanding Big Data Analytics Capabilities in Supply Chain Management: Unravelling the Issues, Challenges and Implications for Practice." Transportation Research Part E: Logistics and Transportation Review 114: 416–36.
[20] Hazen, Benjamin T, Christopher A Boone, Jeremy D Ezell, and L Allison Jones-Farmer. 2014. "Data Quality for Data Science, Predictive Analytics, and Big Data in Supply Chain Management: An Introduction to the Problem and Suggestions for Research and Applications." International Journal of Production Economics 154: 72–80.
[21] Tao, Fei, Qinglin Qi, Ang Liu, and Andrew Kusiak. 2018. "Data-Driven Smart Manufacturing." Journal of Manufacturing Systems 48: 157–69.
[22] Kambatla, Karthik, Giorgos Kollias, Vipin Kumar, and Ananth Grama. 2014. "Trends in Big Data Analytics." Journal of Parallel and Distributed Computing 74 (7): 2561–73.
[23] Witkowski, Krzysztof. 2017. "Internet of Things, Big Data, Industry 4.0--Innovative Solutions in Logistics and Supply Chains Management." Procedia Engineering 182: 763–69.
[24] Dubey, Rameshwar, Angappa Gunasekaran, Stephen J Childe, Constantin Blome, and Thanos Papadopoulos. 2019. "Big Data and Predictive Analytics and Manufacturing Performance: Integrating Institutional Theory, Resource-Based View and Big Data Culture." British Journal of Management 30 (2): 341–61.

[25] Wang, Yichuan, LeeAnn Kung, and Terry Anthony Byrd. 2018. "Big Data Analytics: Understanding Its Capabilities and Potential Benefits for Healthcare Organizations." Technological Forecasting and Social Change 126: 3–13.
[26] Kwon, Ohbyung, Namyeon Lee, and Bongsik Shin. 2014. "Data Quality Management, Data Usage Experience and Acquisition Intention of Big Data Analytics." International Journal of Information Management 34 (3): 387–94.
[27] Manavalan, Ethirajan, and Kandasamy Jayakrishna. 2019. "A Review of Internet of Things (IoT) Embedded Sustainable Supply Chain for Industry 4.0 Requirements." Computers \& Industrial Engineering 127: 925–53.
[28] Akter, Shahriar, Samuel Fosso Wamba, Angappa Gunasekaran, Rameshwar Dubey, and Stephen J Childe. 2016. "How to Improve Firm Performance Using Big Data Analytics Capability and Business Strategy Alignment?" International Journal of Production Economics 182: 113–31.
[29] Chen, Daniel Q, David S Preston, and Morgan Swink. 2015. "How the Use of Big Data Analytics Affects Value Creation in Supply Chain Management." Journal of Management Information Systems 32 (4): 4–39.