Journal of Procurement & Supply Chain

Effect of Machine Learning Model on Supply Chain Performance. A Case of Dubai Port (DP) World/Kigali-Rwanda

Eric KAMANZI & Dr. AKUMUNTU Joseph

ISSN: 2617-3581

Stratford Peer Reviewed Journals and Book Publishing
Journal of Procurement & Supply Chain
Volume 8||Issue 1||Page 13-26 ||January||2024|
Email: info@stratfordjournals.org ISSN: 2617-3581

Effect of Machine Learning Model on Supply Chain Performance. A Case of Dubai Port (DP) World/Kigali-Rwanda

Eric KAMANZI[1] & Dr. AKUMUNTU Joseph[2]
[1] Master of Science in Procurement and Supply Chain Management, University of Kigali, Rwanda
[2] Senior Lecturer, University of Kigali, Rwanda

***How to cite this article*: KAMANZI E., & AKUMUNTU J. (2024). Effect of Machine Learning Model on Supply Chain Performance. A Case of Dubai Port (DP) World/Kigali-Rwanda. *Journal of Procurement & Supply Chain. Vol* 8(1) pp. 13-26** https://doi.org/10.53819/81018102t2311

Abstract

The purpose of this study was to analyse the effect of machine learning model on supply chain performance. Despite this, Dubai Port (DP) World, as a warehouse company, currently faces the challenge of a lack of effective AI explain ability through learning machines together with limited employees in modern AI technology, which is crucial for a successful transition into machine learning for a leading provider of smart logistics solutions, enabling the flow of trade across the globe. In conducting this research, three objectives were laid out to effect of machine learning demand forecasting & planning on supply chain performance in Dubai Port World/Kigali-Rwanda, to assess the effect of machine learning optimization practices on supply chain performance in DP World/Kigali-Rwanda and lastly to determine the effect of machine learning automation on supply chain performance in DP World/Kigali-Rwanda. To achieve these objectives, literature was reviewed on the subject matter including definitions of key concepts, conceptual review, theoretical framework, conceptual framework and research gap analysis. This study based on contingency theory, information processing theory, and practice-based view, additionally researcher applied the universal census by selecting all 131 employees from Dubai Port (DP) World/Kigali, Rwanda. Questionnaire, interview guide and documentation were used as tools of data collection. Data was processed through editing, coding and tabulation and the data also was analyzed by using descriptive statistics. The R value of 0.852 indicates a strong relationship between the predictors and the Supply chain performance in DP World/Kigali-Rwanda. The R Square value of 0.725 indicates that approximately 72.5% of the variability in the outcome variable can be explained by the predictors in the model. Machine learning demand forecasting planning has a coefficient of (β= 0.454, t=8.230, p value=0.000), machine learning optimization practices has a coefficient of (β= 0.252 t=4.125, p value=0.000), and machine learning automation has a coefficient of (β= 0.357, t=6.025, p value=0.000). All these coefficients are statistically significant on supply chain performance in DP World/Kigali-Rwanda, as indicated by their associated Sig. Values below 0.05. Therefore, inline of findings researcher recommended that DP World/Kigali, Rwanda should continue to leverage modern technologies such as Robotic Process Automation (RPA) and Intelligent Document Processing (IDP) to automate shop floor and back-office software-driven processes.

Key words*:* *Machine learning model, supply chain performance and DP World/Kigali, Rwanda.*

Stratford Peer Reviewed Journals and Book Publishing
Journal of Procurement & Supply Chain
Volume 8||Issue 1||Page 13-26 ||January||2024|
Email: info@stratfordjournals.org ISSN: 2617-3581

1. Introduction

1.1. Background of the study

Supply chains (SCs) often span the globe and include manufacturing, trading, and logistics organizations around the world (Zijm and Klumpp, 2016). From a business perspective, SC focuses on the management and synchronization of three flows, namely product flow from suppliers to end customers, financial cash flow from customers to suppliers, and information flow connecting suppliers and customers (Ayan *et al.*, 2022). From the perspective of a business unit, SC represents not only products, but also the entire organization, personnel, resources and even service systems (Arsovski *et al.*, 2017). To achieve this level of complexity, SCM solutions are typically designed to support all key processes within and between different functions within a business organization. For example, philosophy is an important part of how a machine or physical system learns and behaves according to a set of rules. Mathematics provides a formal representation of these rules based on algorithms and probability. Cognitive science involves the study of how people think and behave. When applied to artificial intelligence, it shows how computers think and learn different things. Linguistics studies the relationship between language and thought (Helo and Hao, 2022). Neuroscience is the study of brain function and the similarities between brains and computers. The scientific aspect of artificial intelligence attempts to explain true human intelligence.

In advanced economies like the United States, these transformative technologies can support supply chain management companies in several important ways. It will be interesting to explore AI use cases in different areas. As one of the largest retailers, Walmart uses its artificial intelligence capabilities to process large amounts of data. "Social Genome" is a big data analysis solution developed by Walmart to provide customers with better services by analyzing their activities on various social media. By gaining a deep understanding of customer preferences and behaviors, Walmart is able to inform its direct target customers about products (Zamani *et al.*, 2022). In addition, compared with traditional "rules-based software programming", the core of artificial intelligence is to ensure that machines can define and train models, develop features or variables, optimize parameters, recreate models, retrain and update models (Davenport, 2018) . Artificial intelligence technology is widely used to extract useful information from data. These technologies provide systems with the intelligence to automatically learn and adapt to changing environments by being trained using historical experience (Lee *et al.* 2019).

China and India are both newly industrialized countries. Modern machines with artificial intelligence platforms are able to collect information from their surroundings; using logic and probability, they select transactions with the highest probability of success. These machines should learn to act intelligently based on large amounts of data and recognize objects or sounds with considerable accuracy (Fosso Wamba and Queiroz, 2021). With the advancement of technologies such as mobile computing, Internet big data storage, cloud-based machine learning, and information processing algorithms, the application and benefits of artificial intelligence technology have grown exponentially (Dash *et al.*, 2019). AI-driven machines can perform many tasks, such as recognizing complex patterns, synthesizing information, making conclusions and predictions, which until recently were thought to require human cognition (Dogru and Keskin, 2020).

In a regional context, The most valuable contribution of artificial intelligence to African trade is to drive innovation in all aspects of the African supply chain complex. With the inclusion of the African Continental Free Trade Agreement (AfCFTA) in January 2021, 50 million Africans will have a real chance of escaping extreme poverty by 2035. Artificial intelligence, machine

learning, and the Internet of Everything are, in different ways, important sources of knowledge generation in many other fields. When uncertainty plays an important role, artificial intelligence solves supply chain problems more effectively than other information technology methods (Dubey et al. 2021). Researchers believe that the widespread application of artificial intelligence is critical to how industrial supply chains develop in the future. 4.0. Machine learning is the process of extracting patterns and features directly from data and using algorithms to perform operations, known as "artificial intelligence" (AI) (Rege, 2023).

Rwanda has set up an artificial intelligence development center to help the government create "faster and more flexible ways" to use new technologies. According to Hefner *et al.* (2021); The information processing capability (IPC) of an AI system can be assessed at three IPT levels: leverage, expansion, and exploration. These values indicate how likely AI systems are to replace and supplement human decision-making. Rwanda's cabinet recently approved a national policy on artificial intelligence (AI). According to reports, Rwanda aims to use artificial intelligence, digital and new technologies to support development goals, become an ICT and innovation hub, and put the country in a leading position. Furthermore, the policy framework reportedly aims to accelerate the adoption of AI by supporting the rapid growth of Rwanda's AI ecosystem, encouraging the adoption of AI in high-growth industries, and encouraging increased public and private investment in AI.

1.2. Statement of the problem

Advanced technologies have enabled the digitization of almost all operational processes to control manufacturing throughout the supply chain (Schiavone and Sprenger, 2017). Machine learning in the supply chain industry can enable more accurate inventory management, which helps predict demand. Machine learning is used for inventory optimization to promptly detect over- or under-stocking of assets in stores (Mostafa, 2020). Digitalization of logistics, including improved tracking systems, digital information flows, artificial intelligence and automation, has further facilitated global trade. Artificial intelligence is helping Rwandan logistics companies find the most cost-effective and efficient ways to achieve this goal. Through IA, DP World begins offering an end-to-end freight tracking solution that seamlessly integrates data from all logistics providers to increase efficiency, reduce costs and improve customer experience, bringing unparalleled transparency and predictability to the logistics industry.

Despite this, Dubai Port (DP) World, as a warehouse company, currently faces the challenge of a lack of effective machine learning through learning machines demand forecasting & planning, and both on ML optimization and automation practices together with limited employees in modern AI technology, which is crucial for a successful transition into machine learning for a leading provider of smart logistics solutions, enabling the flow of trade across the globe. In addition, inadequate policy frameworks, huge infrastructure deficits and trade barriers have led to compromised supply chain performance, negatively impacting Rwanda's economic growth. Overall, Rwanda, as a coastal country, is highly dependent on imports of food, machinery and equipment, construction materials, petroleum products and fertilizers. There is a need to leverage artificial intelligence as the latest technology for proper supply chain management, but as seen in the past few years, prices have increased so much that business has been poor; even storage companies have been struggling to attract more customers. In supply chains, AI is used to automate tasks, predict demand, optimize routes, manage inventory, and even monitor safety and compliance. These capabilities are critical for companies that want to stay ahead of the competition and meet customer needs (Hefner *et al*., 2021).

According to Tirkolaee *et al.* (2021), machine learning in logistics is the use of advanced statistical models to optimize route decisions, predict material and inventory requirements, automate order fulfillment, reduce transportation costs, predict supply chain disruptions, and identify customer demand patterns. Researchers note that many companies make short-term forecasts and focus on strengthening supply chain capabilities (Siegrist, 2021). To do this, these companies must regularly assess their risk levels based on several parameters. From the above statement, the researcher needed to conduct this study that focused on the effect of a machine learning model on supply chain performance in the case of Dubai Port.

1.3. Objectives of the study

The general objective was to analyse the effect of machine learning model on supply chain performance.

Specific objectives

i. To find out the effect of machine learning demand forecasting & planning on supply chain performance in Dubai Port World/Kigali-Rwanda.
ii. To assess the effect of machine learning optimization practices on supply chain performance in Dubai Port World/Kigali-Rwanda.
iii. To determine the effect of machine learning automation on supply chain performance in Dubai Port World/Kigali-Rwanda.

1.4. Research hypothesis

Hypotheses allow researchers to not only discover relationships between variables but also predict relationships based on theoretical guidance and empirical evidence (Friston *et al.*, 2016). Formulating a hypothesis requires a thorough understanding of the research topic and a thorough review of prior literature.

Ho_1: There is no significant relationship between machine learning demand forecasting & planning on supply chain performance in Dubai Port World/Kigali-Rwanda.

Ho_2: There is no significant relationship between machine learning optimization practices and supply chain performance in Dubai Port World/Kigali-Rwanda.

Ho_3: There is no significant relationship between machine learning automation and supply chain performance in Dubai Port World/Kigali-Rwanda.

2. Literature review

2.1. Theoretical review

A theoretical literature review helps determine which theories already exist, what relationships exist between them, how well existing theories are researched, and suggest new hypotheses to test. Therefore, this section introduces contingency theory, information processing theory, and practice-based view.

2.1.1. Contingency theory (CT)

“As operations management (OM) best practices have matured, interest in practice research has shifted from demonstrating the value of these practices to understanding the contextual conditions in which they operate. Eckstein et al. (2015) consider CT as a mediating theory , aims to identify situations in the organizational environment that affect performance. CT believes that organizations should adapt their structures and practices to fit the environment in

which the organization operates (Donaldson, 2001). CT explains the context in which operations management practices can improve organizational performance.

Kunz and Gold (2017) argue that humanitarian action aims to alleviate the suffering of victims in the shortest possible time and with limited resources. In this case, it is important to remember that when providing relief supplies to affected people: Disaster relief workers should consider local conditions. The design of humanitarian supply chains should not only be guided by the structure of aid organizations, but also consider the long-term needs of local populations and all socioeconomic and government emergencies (Salam and Khan, 2020). Therefore, in line with the principles of CT, we argue that, under certain conditions, the practices of humanitarian organizations can provide better explanations for improving humanitarian supply chain performance.

Contingency theory suggests that there is no one-size-fits-all approach to managing organizations or systems. In this context, machine learning demand forecasting and planning align with contingency theory by acknowledging that supply chain strategies should be contingent upon environmental factors, such as market demand fluctuations, regional variations, and changing customer preferences. By leveraging machine learning for forecasting and planning, organizations like Dubai Port World or Kigali-Rwanda adapt their supply chain strategies based on contingent factors, leading to improved performance in meeting demand variability.

2.1.2. Information processing theory

Information processing theory is a cognitive framework developed by American psychologists George A. Miller and Richard Shifflin in the 1960s that explains how the human mind processes, stores, and retrieves information (Egelhoff, 1991). This theory states that our cognitive abilities are based on the interplay of sensory memory, short-term memory, and long-term memory. These components work together to help us encode, store, and retrieve information efficiently. One of the key figures in the theory, George Miller, introduced the concept of parallel processing, where our brains process multiple pieces of information at the same time. This concept has greatly influenced our understanding of human memory and led to the development of more advanced models of information processing.

Information processing theory uses a processing approach that emphasizes the importance of examining the psychological processes involved in learning, such as attention, cognition, and memory (Rogers et al. 1999). This approach enables researchers and educators to better understand the complex mechanisms behind human learning and develop more effective teaching strategies. By focusing on mental processes, information processing theory has greatly contributed to our understanding of human memory, including the organization, storage, and retrieval of information. Therefore, the theory is often used by educational institutions to understand and improve human learning. It provides educators with valuable insights into the cognitive processes of learning, allowing them to tailor instruction to the needs of individual learners and promote better learning outcomes.

OIPT believes that organizations develop within a system that integrates multiple internal and external processes and is characterized by complexity and uncertainty (Spender and Kessler, 1996). The theory provides a solid foundation for explaining the concept and organizational behavior of the firm through information processing mechanisms. Gattiker and Goodhue (2004) identified several sources of uncertainty, such as: hierarchical references and standard operating procedures, instability in the supply chain environment, and the degree of interdependence between subunits. As the amount of data managed by organizations increases,

so does the use of information processing, requiring the involvement of multiple internal and external entities (Galbraith, 1984; Srinivasan & Swink, 2018). Such large amounts of data require greater transparency to ensure effective decision-making.

According to Huang *et al*. (2015), an organization's ability to process data can be improved by improving the culture of sharing mutually beneficial cross-organizational information, thereby improving the collaborative environment and reducing the uncertainty associated with coordination. Premkumar (2000) adds that a lack of information processing culture in an uncertain environment imposes huge costs on organizations. Recent research has found that the ability to process information can improve performance and increase a company's competitive advantage (Bartnik and Park, 2018; Dubey *et al.*, 2019b). In healthcare, knowledge-based information processing capabilities and the use of appropriate technologies can improve operational management and patient service quality (Srivastava and Singh, 2020). Various studies point to the role of technological infrastructure as a mechanism that can enhance an organization's information processing capabilities.

Against this background, we believe that the use of BDA artificial intelligence technology can help enterprises cultivate and utilize the additional information required for internal and external supply chain decision-making. This study supports previous studies that examine companies' use of information technologies such as BDA and enterprise resource planning (ERP) to improve information processing capabilities, often based on the OIPT approach (Dubey *et al.*, 2019). In private logistics companies, supply chain operations depend on several uncertain conditions that vary according to patient needs and the unpredictability of medical activities. These uncertainties or disruptions may complicate the ability to effectively process information and make decisions about implementing environmental approaches. In addition, there is a high degree of interdependence between units in various ports, adding to organizational complexity. In this regard, the use of BDA can be very helpful in supporting the decision-making process by taking steps to improve hospital EP. However, given the complexity of healthcare supply chains, including different groups, operations, and stakeholders (Ageron *et al.*, 2018), there is evidence that BDA-AI is capable of processing environmental information across the entire port supply chain as intended.

Information processing theory revolves around how organizations process information to make decisions and improve performance. Machine learning optimization practices align with this theory by emphasizing the use of algorithms and data-driven insights to optimize supply chain processes. By applying machine learning techniques for optimization, organizations can efficiently process large volumes of data, analyze patterns, and make informed decisions to enhance supply chain efficiency, minimize costs, and improve overall performance.

2.1.3. Practice-based view (PBV)

The practice-based perspective (PBV) is a relatively new perspective proposed by Bromiley and Rau (2014) as an alternative to the resource-based perspective (RBV) (see Barney, 1991; Peteraf, 1993). The logic behind PBV is that even small day-to-day activities of a business or organization can impact its performance. RBV and DCV attempt to explain how a firm's resources or capabilities produce or help maintain high organizational performance (Bag *et al.*, 2021). Nonetheless, Bromiley and Rau (2014) argued that the theory of competitive advantage only applies to a small number of companies in an industry, and those average companies that make small but significant improvements do not meet the eligibility criteria for applying the RBV/DCV of competitive advantage. Advantages realized.

Furthermore, RBV or DCV focuses on explanatory variables that lead to competitive advantage (Kov´acs and Tatham, 2009). However, humanitarian relief efforts involve actors from various

organizations who assist victims by providing them with necessary supplies and shelter. Against this backdrop, humanitarian action management scholars need to focus on common practices that can improve humanitarian supply chain performance. Scholars generally agree that managing humanitarian supply chains is a simple application of the practices of managing commercial supply chains. However, some scholars believe that despite some similarities, these two types of supply chains differ significantly in their objectives (Holguín-Veras *et al.*, 2012). Therefore, different skills are required to manage humanitarian supply chains efficiently and effectively (e.g. Charles *et al.*, 2010; Holguín-Veras *et al.*, 2012).

Compared to commercial supply chains, losses in humanitarian supply chains are not measured by increased distribution costs or poor on-time delivery (Tatham and Kovacs, 2010). Lack of effectiveness or inefficiency can cause losses and negatively impact the lives of vulnerable people stranded in disaster areas. Therefore, RBV or DCV theory seems insufficient to explain the performance of humanitarian supply chains. For example, the idea of RBV is based on the assumption that resources that help create or maintain competitive advantage must be valuable, scarce, difficult to imitate, and irreplaceable (V, R, I, N) (Barney, 1991) ;Petrav, 1993). However, it is difficult to imagine that the same resources that provide businesses with a competitive advantage could also be used for humanitarian relief efforts. Humanitarian supply chains tend to emerge quickly, with actors working on a voluntary basis (Tatham and Kovacs, 2010). Therefore, PBV is more applicable because it focuses on sharing practices and results. Likewise, DCV focuses on the ability to integrate, build, and reconfigure internal and external capabilities. Create capabilities that help organizations maintain a competitive advantage in highly dynamic or unstable environments. However, in order to create such capabilities, companies must approach it as a long-term project that requires significant investment. However, humanitarian supply chains are mostly short-term projects that require immediate response. Here too, PBV makes more sense than DCV.

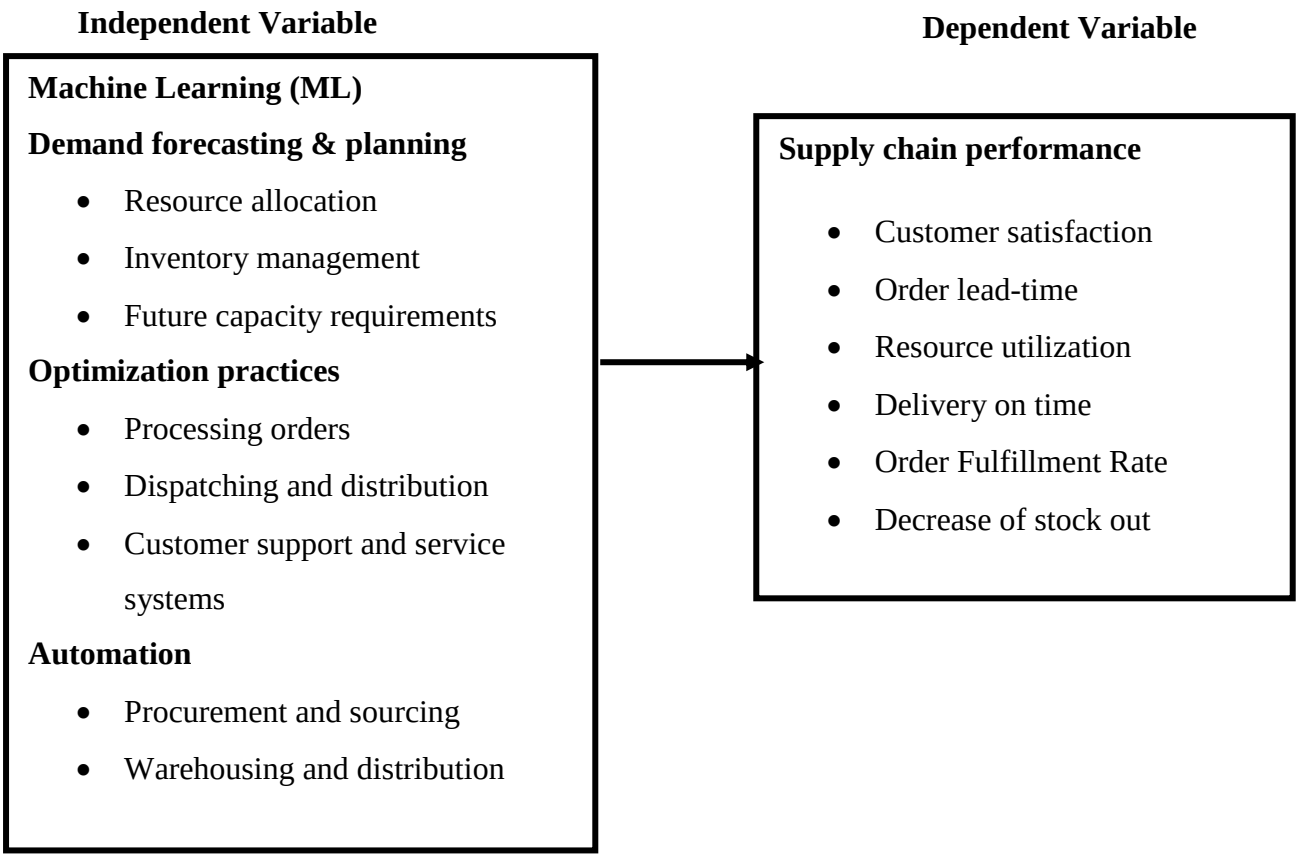
The practice-based view theory focuses on how organizations develop and leverage internal capabilities and practices to achieve superior performance. Machine learning automation in the supply chain aligns with this theory by emphasizing the development and integration of automated processes within the organizational practices. By adopting machine learning automation, Dubai Port World or Kigali-Rwanda enhances its operational capabilities, streamlines workflows, and improves performance by relying on advanced technology-enabled practices.

2.2. Conceptual framework

A conceptual framework is a schematic diagram used to identify variables that jointly explain a problem (Ali *et al.* , 2012). In this case, the independent variable is related to machine learning model and the dependent variable is related to supply chain performance as follows:

Stratford Peer Reviewed Journals and Book Publishing
Journal of Procurement & Supply Chain
Volume 8||Issue 1||Page 13-26 ||January||2024|
Email: info@stratfordjournals.org ISSN: 2617-3581

Figure 1: Conceptual framework



Source: Researcher (2023)

Figure 1 indicated that machine learning model applied by Dubai Port (DP) World is done through demand forecasting and planning, optimization, and automation and this influences supply chain performance through customer satisfaction, order lead-time, finally resource utilization, Delivery on time, Order Fulfillment Rate and decrease of stock out.

3. Research methodology

This chapter focused on the research design and methods that researcher used to collect and analyses data.

3.1 Research design

Both descriptive and correlational research designs present the findings/or results of the respondents in the form of frequencies, percentages, means and standard deviations through measures of central tendency.

3.2 Population and sample size of the study

The study covers DP World/Kigali-Rwanda's employees and consists of 131 employees including the Management Team, Technical Operations Department, Legal and Secretarial Department, Compliance Department, Drydock World, International Ports and Terminals, Planning and Projects Department and Digital Division Technology, Supply Chain and Logistics, Talent Acquisition, Human Resources and Sustainability, Audit and Compliance Division and Finance Division, Finance and Accounting Division, Procurement Management, Sales and Marketing Division, Logistics Division, Customer Service Management, Warehouse and inventory management, coordination and logistics

Stratford Peer Reviewed Journals and Book Publishing
Journal of Procurement & Supply Chain
Volume 8||Issue 1||Page 13-26 ||January||2024|
Email: info@stratfordjournals.org ISSN: 2617-3581

The study used universal census, the researcher chose to talk to everyone in the group under study because there aren't too many people. Researcher want to gather information from every single person or unit in that group, not just a few selected ones. This way, the researcher hopes to get a really good and complete understanding of the whole group they're investigating.

3.3. Data collection instruments

Under this section the researcher used both questionnaire and documentation.

3.3.1. Questionnaire

The questionnaire consisted of closed-ended questions. Additionally, these questions are questions that limit the respondent's answers or opinions through pre-selected options. Questionnaires were used as data collection technique as they are easy to administer and save time.

3.3.2. Documentation

The researcher used documentation to get theories useful for the research; this was also used to attain much information regarding the effect of machine learning model on supply chain performance with reference to Dubai Port (DP) World. It required us to consult all different books and internet websites related to how DP World works as a business organization specialized in the effect of machine learning model on supply chain performance.

3.4. Data analysis

Quantitative data was entered in SPSS from where it was analyzed. Descriptive statistics, mainly percentages were generated. In addition, the effect of machine learning model on supply chain performance was analyzed through the case of Dubai Port in Rwanda. As a solution to this problem, researcher also prefer multiple regression models that assume a linear relationship $Y = \alpha + \beta X + \varepsilon$ between the dependent variable Y (supply chain performance) and the explanatory variable X (machine learning model), where the error term ε includes the omitted factor. Check as follows:

$$Y = a + bX_1 + cX_2 + dX_3 + \epsilon$$

Where:

- **Y** : Supply Chain Performance
- **X_1, X_2, X_3**: Independent (explanatory) variables: ML demand forecasting & planning (x_1), ML optimization practices (x_2) and ML automation on (x_3).
- **A** : Intercept
- **b, c, d**: Slopes
- **ϵ** : Residual (error)

Multiple linear regressions follow the same conditions as the simple linear model.

Stratford Peer Reviewed Journals and Book Publishing
Journal of Procurement & Supply Chain
Volume 8||Issue 1||Page 13-26 ||January||2024|
Email: info@stratfordjournals.org ISSN: 2617-3581

4. Research findings

Inferential statistics help to come up with explanations for situations or phenomena. It allows researchers to draw conclusions based on extrapolation, and is fundamentally different from descriptive statistics, which simply summarizes actually measured data.

Table 1: Correlations

		Machine learning demand forecasting & planning	Machine learning optimization practices	Machine learning automation	Supply chain performance
Machine learning demand forecasting & planning	Pearson Correlation	1	.526**	.471**	.736**
	Sig. (2-tailed)		.000	.000	.000
	N	131	131	131	131
Machine learning optimization practices	Pearson Correlation	.526**	1	.686**	.736**
	Sig. (2-tailed)	.000		.000	.000
	N	131	131	131	131
Machine learning automation	Pearson Correlation	.471**	.686**	1	.734**
	Sig. (2-tailed)	.000	.000		.000
	N	131	131	131	131
Supply chain performance	Pearson Correlation	.736**	.736**	.734**	1
	Sig. (2-tailed)	.000	.000	.000	
	N	131	131	131	131

**. Correlation is significant at the 0.01 level (2-tailed).

In Table 1, strong positive correlations are evident between various Machine Learning practices and Supply chain performance). Machine learning demand forecasting planning exhibits a strong positive correlation of 0.736, highlighting that well-structured machine learning demand forecasting & planning is closely linked to better Supply chain performance in in DP World/Kigali-Rwanda. Similarly, machine learning optimization practices shows a strong positive correlation of 0.736, indicating that effective machine learning optimization practices contributes significantly to improved Supply chain performance in in DP World/Kigali-Rwanda. Lastly, machine learning automation demonstrates a positive correlation of 0.734, emphasizing the importance of machine learning automation in Supply chain performance in DP World/Kigali-Rwanda. These correlations, all statistically significant at the 0.05 level, collectively indicates that enhancements in Machine Learning, machine learning automation, machine learning demand forecasting & planning, and machine learning optimization practices are associated with improved overall Supply chain performance in DP World/Kigali-Rwanda.

The findings supported by the emphasis of Ning & You (2019) that Machine learning programming involves modeling previously known data and desired outcomes to discover a previously unknown set of rules. This relatively new method of problem solving is very useful in business in general and supply chain management in particular. This aligns well with the

Stratford Peer Reviewed Journals and Book Publishing
Journal of Procurement & Supply Chain
Volume 8||Issue 1||Page 13-26 ||January||2024|
Email: info@stratfordjournals.org ISSN: 2617-3581

fact that, enhancements in Machine Learning, machine learning automation, machine learning demand forecasting planning, and machine learning optimization practices are associated with improved overall Supply chain performance in DP World/Kigali-Rwanda.

Table 2: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.852[a]	.725	.719	.34526

a. Predictors: (Constant), machine learning automation, machine learning demand forecasting & planning, machine learning optimization practices

Table 2 presents the model summary for a regression analysis. The model includes predictors such as machine learning automation, machine learning demand forecasting & planning, machine learning optimization practices. The R value of 0.852 indicates a strong relationship between the predictors and the supply chain performance in DP World/Kigali-Rwanda. The R Square value of 0.725 indicates that approximately 72.5% of the variability in the outcome variable can be explained by the predictors in the model. Overall, this model summary indicates a significant relationship between the Machine Learning practices and the outcome variable supply chain performance in DP World/Kigali-Rwanda, with a good fit to the data.

The findings are consistent with the observations of Soleimani (2018) that AI technologies can achieve four identified properties in SC: optimization, prediction, modeling and simulation, and decision support. This aligns with the fact that there is a strong relationship between the Machine Learning predictors and the supply chain performance in DP World/Kigali-Rwanda.

Table 3: ANOVA

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	40.008	3	13.336	111.879	.000[b]
	Residual	15.139	127	.119		
	Total	55.147	130			

a. Dependent Variable: Supply chain performance
b. Predictors: (Constant), machine learning automation, machine learning demand forecasting & planning, machine learning optimization practices

The F-statistic in Table 3, with an F value of 111.879, indicates the results of an Analysis of Variance (ANOVA) for the regression model. The associated significance level (Sig.), denoted as .000, is less than the typical significance threshold of 0.05. This implies that the overall model, which includes predictors like machine learning automation, machine learning demand forecasting & planning, machine learning optimization practices, is statistically significant. In simpler terms, there is strong evidence to assume that at least one of the predictors in the model has a significant impact on the dependent variable, supply chain performance in DP World/Kigali-Rwanda, with a good fit to the data. This indicates the importance of these Machine Learning factors in influencing supply chain performance in DP World/Kigali-Rwanda, with a good fit to the data.

The findings supported by the emphasis of Dubey *et al.* (2021) that when uncertainty plays an important role, artificial intelligence solves supply chain problems more effectively than other information technology methods. This support the fact that Machine Learning factors in influencing supply chain performance in DP World/Kigali-Rwanda, with a good fit to the data.

Stratford Peer Reviewed Journals and Book Publishing
Journal of Procurement & Supply Chain
Volume 8||Issue 1||Page 13-26 ||January||2024|
Email: info@stratfordjournals.org ISSN: 2617-3581

Table 4: Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.038	.197		-.192	.848
	Machine learning demand forecasting & planning	.454	.055	.447	8.230	.000
	Machine learning optimization practices	.252	.061	.248	4.125	.000
	Machine learning automation	.357	.059	.350	6.025	.000

a. Dependent Variable: Supply chain performance

As a solution to this problem, researcher also prefer multiple regression models that assume a linear relationship $Y = \alpha + \beta X + \varepsilon$ between the dependent variable Y (supply chain performance) and the explanatory variable X (machine learning model), where the error term ε includes the omitted factor. Check as follows:

$$Y = a + bX_1 + cX_2 + dX_3 + \epsilon$$

Supply Chain Performance = -0.038 + 0.454 machine learning demand forecasting & planning + 0.252 machine learning optimization practices + 0.357 machine learning automation + 0.197

In Table 4, the constant term, representing the estimated intercept of the regression model, has an unstandardized coefficient of -0.038 with a standard error of 0.197, and it is not statistically significant with a Sig. Value of 0.848. The unstandardized coefficients for the predictor variables show their individual impacts on Supply chain performance. Specifically, machine learning demand forecasting & planning has a coefficient of (β= 0.454, t=8.230, p value=0.000), machine learning optimization practices has a coefficient of (β= 0.252 t=4.125, p value=0.000), and machine learning automation has a coefficient of (β= 0.357, t=6.025, p value=0.000). All these coefficients are statistically significant on supply chain performance in DP World/Kigali-Rwanda, as indicated by their associated Sig. Values below 0.05.

Hypotheses summary results

The results of the hypotheses testing in Table 5 provide significant overviews into the influence of Machine Learning on supply chain performance of Dubai Port World/Kigali-Rwanda. Each null hypothesis (Ho1, Ho2, or Ho3) has been rejected ($p < 0.05$), indicating strong evidence against the idea that these Machine Learning practices have no significant effect on the supply chain performance of Dubai Port World/Kigali-Rwanda. Specifically, machine learning demand forecasting & planning, machine learning optimization practices, and machine learning automation, all demonstrate a significant influence on the supply chain performance of Dubai Port World/Kigali-Rwanda. These findings emphasize the critical role of comprehensive Machine Learning in achieving the supply chain performance of Dubai Port World/Kigali-Rwanda.

5. Conclusion

Based on the comprehensive analysis of correlations, regression analysis, model summaries, and hypothesis testing concerning machine learning practices and supply chain performance in DP World/Kigali-Rwanda, it's evident that a strong positive relationship exists between machine learning components (demand forecasting & planning, optimization practices, and automation) and supply chain performance. The correlations showcase robust positive

associations, indicating that well-structured machine learning practices significantly influence the supply chain's effectiveness in DP World/Kigali-Rwanda. The rejection of null hypotheses and the strong statistical significance of machine learning predictors emphasize their substantial impact on supply chain performance, underscoring the critical role of comprehensive and effective machine learning models in achieving a more efficient and effective supply chain in DP World/Kigali-Rwanda.

6. Recommendations

Basing on the research findings, the researcher recommended that:
DP World-Rwanda can effectively match its machine learning supply and demand by accurately forecasting, minimizing waste and streamlining processes.
DP World - Rwanda should work with partners in the supply chain to continuously improve planning, build trust and promote cooperation.
DP World/Kigali, Rwanda should continue to leverage modern technologies such as Robotic Process Automation (RPA) and Intelligent Document Processing (IDP) to automate shop floor and back-office software-driven processes.

Acknowledgement

My research for this thesis brought me into contact with several participants. I owe specific gratitude to anyone who helped in the process of this research and how he/she contributed. I am greatly indebted to my supervisor, Dr. AKUMUNTU Joseph for his excellent academic guidance and his confidence in my ability to carry out the research. Special thanks are extended to my family for their patience and encouragement throughout my stay at University of Kigali. My thanks also go to my classmates and friends. Finally, to God is the glory for His wondrous gifts of health, ingenuity and grace to the point of the submission.

References

Arsovski, S., Arsovski, Z., Stefanović, M., Tadić, D., & Aleksić, A. (2017). Organisational resilience in a cloud-based enterprise in a supply chain: a challenge for innovative SMEs. *International Journal of Computer Integrated Manufacturing*, *30*(4-5), 409-419.

Batrinca, B., Hesse, C. W., & Treleaven, P. C. (2017). Developing a volume forecasting model. *Journal of Applied Finance and Banking*, *7*(1), 1.

Chowdhary, K. R. (2020). *Fundamentals of artificial intelligence* (pp. 603-49). New Delhi:: Springer India.

Dash, R., McMurtrey, M., Rebman, C., & Kar, U. K. (2019). Application of artificial intelligence in automation of supply chain management. *Journal of Strategic Innovation and Sustainability*, *14*(3),

Datta, S. (2017). Sourcing, supply chain, and manufacturing of nutraceutical and functional foods. In *Developing new functional food and nutraceutical products* (pp. 179-193). Academic Press.

Friston, K., Adams, R. A., Perrinet, L., & Breakspear, M. (2016). Perceptions as hypotheses: saccades as experiments. *Frontiers in psychology*, *3*, 151.

Grover, A. K., & Dresner, M. (2022). A theoretical model on how firms can leverage political resources to align with supply chain strategy for competitive advantage. *Journal of Supply Chain Management*, *58*(2), 48-65.

Guo, K., Yang, Z., Yu, C. H., & Buehler, M. J. (2021). Artificial intelligence and machine learning in design of mechanical materials. *Materials Horizons*, *8*(4), 1153-1172.

Gupta, S., Modgil, S., Gunasekaran, A., & Bag, S. (2020). Dynamic capabilities and institutional theories for Industry 4.0 and digital supply chain. In *Supply Chain Forum: An International Journal* (Vol. 21, No. 3, pp. 139-157). Taylor & Francis.

Guzman, A. L., & Lewis, S. C. (2020). Artificial intelligence and communication: A human–machine communication research agenda. *New media & society*, *22*(1), 70-86.

Howard, J. (2019). Artificial intelligence: Implications for the future of work. *American journal of industrial medicine*, *62*(11), 917-926.

Jain, V., Kumar, S., Soni, U., & Chandra, C. (2017). Supply chain resilience: model development and empirical analysis. *International Journal of Production Research*, 55(22), 6779–6800

Kunz, N., & Gold, S. (2017). Humanitarian Action: Aligning Practices with Local Conditions. *Journal of Humanitarian Logistics and Supply Chain Management*, 24(3), 78-92.

Kwak, N., & Radler, B. (2022). A comparison between mail and web surveys: Response pattern, respondent profile, and data quality. *Journal of official statistics*, *18*(2), 257.

Naz, M., Shah, J. H., Khan, M. A., Sharif, M., Raza, M., & Damaševičius, R. (2021). From ECG signals to images: a transformation based approach for deep learning. *PeerJ Computer Science*, *7*, e386.

Rai, R., Tiwari, M. K., Ivanov, D., & Dolgui, A. (2021). Machine learning in manufacturing and industry 4.0 applications. *International Journal of Production Research*, *59*(16), 4773-4778.

Salam, A., & Khan, M. A. (2020). Designing Humanitarian Supply Chains: Considerations for Local Conditions. *International Journal of Emergency Management*, 15(2), 112-128.

Wadidi, A., Johnson, M. R., Smith, K. L., & Anderson, P. J. (2019). Artificial Intelligence in Supply Chain Management: Autonomy and Decision-Making. *Journal of Advanced Logistics*, 13(2), 45-60.

Wenzel, H., Smit, D., & Sardesai, S. (2019). A literature review on machine learning in supply chain management. In *Artificial Intelligence and Digital Transformation in Supply Chain Management: Innovative Approaches for Supply Chains. Proceedings of the Hamburg International Conference of Logistics (HICL), Vol. 27* (pp. 413-441). Berlin: epubli GmbH.

Yao, W. (2017). *Analysis on the Application of the Artificial Intelligence Neural Network on the New Energy Micro Grid*. Proceedings of the 2017 4th International Conference on Machinery, Materials and Computer (MACMC)

Zhang, A., Lipton, Z. C., Li, M., & Smola, A. J. (2021). Dive into deep learning. *arXiv preprint arXiv:2106.11342*.

Zijm, H., & Klumpp, M. (2016). Logistics and supply chain management: developments and trends. *Logistics and supply chain innovation: Bridging the gap between theory and practice*, 1-20.