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Artificial Intelligence (AI) And Decision-Making In Supply Chain Management Of Lubricant Firms In Anambra State, Nigeria

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ABSTRACT

The integration of artificial intelligence algorithms with predictive analytics has emerged as a critical tool for decision-makers aiming to gain a competitive edge. This study examined the effect of artificial intelligent (AI) on decision-making in supply chain management of lubricant firms in Anambra state, Nigeria. The objective of the study were to; Determine the effect of machine learning on decision support system on supply chain management of lubricant firms in Anambra state; Ascertain the extent to which neural networks affect creative decision skill on supply chain management of lubricant firms in Anambra state; examined the extent to which deep learning affect analytical decision skill on supply chain management of lubricant firms in Anambra State. The study was anchored on Technology Acceptance Theory (TAT). A structure questionnaire was developed for data collection. The population of the study comprised of 281 management staff from thirteen (13) lubricant firms in Anambra State. Two hundred and sixty-nine (269) were duly filled and returned data was analysed using correlation analysis with the aid of statistical package for social science (SPSS) version 23. Findings from the study show that. Machine learning has significant effect on decision support system on supply chain management of lubricant firms in Anambra state (T=2.244, P=0.006). Neural networks has significant effect on creative decision skill on supply chain management of lubricant firms in Anambra state (T=9.790, P=0.009). The study concludes that AI-powered predictive analytics improved decision-making in supply chain management in lubricant firms in Anambra state, Nigerian. The study recommends that Firms should prioritize data collection, storage, and analysis. Technical expertise is critical for implementing and optimizing neural network algorithms. Firms should consider hiring experts or providing training to existing staff.

Keywords: machine learning, decision support system, artificial intelligent, neural networks, and deep learning

INTRODUCTION

In today's rapidly evolving business landscape, predictive analytics has become a pivotal tool for gaining competitive advantage. Predictive analytics involves using statistical techniques, machine learning algorithms, and data mining to analyze current and historical data, enabling businesses to make informed predictions about future events (Fortino, 2023; Hemachandran, Khanra, Rodriguez, & Jaramillo, 2022). This technology's growing importance is underscored by its ability to provide insights that drive strategic decisions, optimize operations, and improve overall business performance. As companies accumulate vast amounts of data, harnessing this information effectively becomes increasingly crucial (Adelakun, Nembe, Oguejiofor, Akpuokwe, & Bakare, 2024; Adenekan, Solomon, Simpa, & Obasi, 2024; Broby, 2022).

In today's data-driven world, businesses are generating vast amounts of information from diverse sources such as customer transactions, social media interactions, market trends, and supply chain operations. Traditional data analysis methods, while effective in many cases, are often limited in their ability to handle the volume, variety, and velocity of this data. To address this challenge, predictive analytics, powered by Artificial Intelligence (AI), has emerged as a transformative tool for businesses looking to gain deeper insights and forecast future trends (Domingos, 2015). Predictive analytics, powered by artificial intelligence (AI), is revolutionizing the decision-making process across industries by offering insights based on advanced data analysis techniques. In the business landscape, strategic insights derived from AI-driven solutions enable organizations to anticipate trends, adapt to dynamic market conditions, and optimize operational processes. Maduagwuna, Anah, & Ohanyere (2023) established that Value Commitment enhances performances since employees performed better when there are informed or communicated to than those who are not informed.

The integration of AI algorithms with predictive analytics has emerged as a critical tool for decision-makers aiming to gain a competitive edge. AI-powered decision-making leverages vast datasets, employing machine learning algorithms to identify patterns and forecast outcomes. This capability allows businesses to transition from reactive to proactive strategies, reducing risks and enhancing overall efficiency. Predictive models enable organizations to anticipate customer behavior, market fluctuations, and operational challenges, transforming raw data into actionable intelligence (Provost & Fawcett, 2013). Predictive analytics involves using historical data to predict future outcomes. It utilizes statistical algorithms, machine learning, and data mining techniques to identify patterns in historical data that can be used to anticipate future events. AI enhances this process by automating the analysis of large and complex datasets and continuously learning from new data, making predictions more accurate and timely (Shmueli & Koppius, 2011).

Statement of the Problem

The evolution of AI has greatly expanded the capabilities of predictive analytics. Machine learning algorithms, a core part of AI, allow systems to learn from data without being explicitly programmed. This means that the more data AI systems process, the better they become at identifying trends and making accurate predictions. Furthermore, AI's ability to process real-time data allows businesses to make decisions based on the most current information available. Artificial intelligence (AI) has become an increasingly crucial technology shaping competitive dynamics in nearly all sectors. Businesses now leverage AIS-driven insights stemming from massive real-time data streams to inform core strategic imperatives and decision-making processes. Despite its transformative potential, AI-driven predictive analytics also presents challenges.

One of the primary challenges in implementing predictive analytics is ensuring data quality and availability. Predictive models rely heavily on accurate, consistent, and comprehensive datasets to deliver reliable outcomes. Incomplete or noisy data can lead to erroneous predictions and hinder strategic decision-making. Again, is the scalability of predictive analytics solutions as this poses another significant hurdles. As businesses grow and data volumes increase exponentially, existing infrastructure may fail to support the computational demands of advanced analytics.

Yet another challenge is the problem of interpreting predictive insights. Even with accurate predictions, the ability to interpret and act on insights remains a critical challenge. Predictive analytics often generates complex outcomes, such as probabilities and statistical relationships, which may not be immediately actionable for decision-makers. Finally, the problem of ethical and regulatory concerns further complicate the implementation of predictive analytics. The use of sensitive customer data requires strict adherence to privacy laws and ethical standards. Non-compliance can lead to reputational damage and legal penalties.

Objectives of the study

The main objective of this study is the use of AI-powered predictive analytics for improved decision-making in supply chain management in lubricant firms in Anambra state, Nigeria. The specific objectives are to

i. Determine the effect of machine learning on decision support system on supply chain management of lubricant firms in Anambra state
ii. Ascertain the extent to which neural networks affect creative decision skill on supply chain management of lubricant firms in Anambra state
iii. Assess the extent to which deep learning affect analytical decision skill on supply chain management of lubricant firms in Anambra state

REVIEW OF RELATED LITERATURE

Conceptual Review

Artificial Intelligence

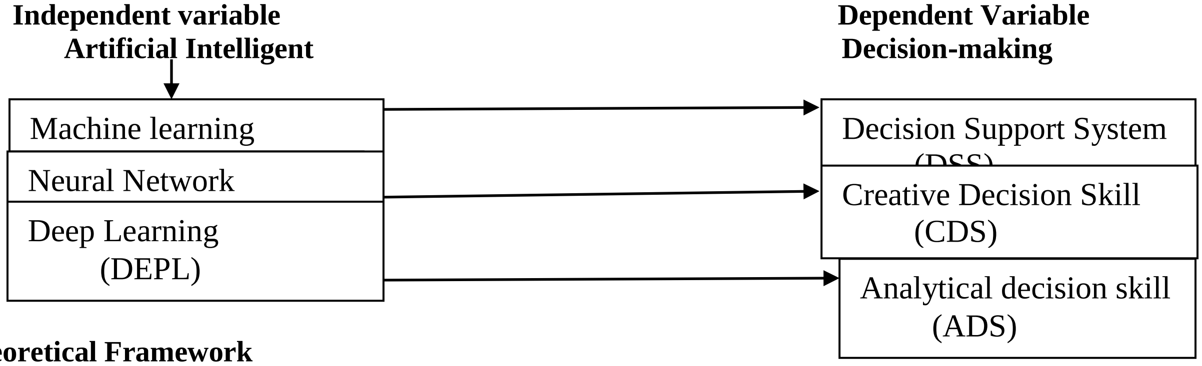
Artificial Intelligence (AI) refers to the simulation of human intelligence processes by computer systems, encompassing learning, reasoning, and self-correction. Specifically, AI systems can acquire information and rules for using it, apply logical deduction to solve problems, and improve their performance through experience (Russell & Norvig, 2016). AI is often categorized into two main types: narrow AI and general AI. Narrow AI, also known as weak AI, is designed to perform specific tasks, such as facial recognition, language translation, or playing chess, effectively mimicking human capabilities in those areas (Bengio et al., 2017).

In contrast, general AI, or strong AI, aspires to possess the ability to understand, learn, and apply intelligence across a broad range of tasks, similar to human cognitive abilities (Goertzel & Pennachin, 2017). AI technologies leverage various techniques, including ML, where algorithms improve their performance based on past data, and deep learning, which utilizes neural networks to analyze complex data patterns (LeCun et al., 2015). The application of AI spans numerous fields, from healthcare and finance to entertainment and transportation. By automating routine tasks, enhancing decision-making processes, and providing predictive insights, AI has become a crucial tool for businesses seeking efficiency and innovation**.**

Decision-making

Decision-making is regarded as the cognitive process resulting in the selection of a belief or a course of action among several possible alternative options. It could be either rational or irrational. The decision-making process is a reasoning process based on assumptions of values, preferences and beliefs of the decision-maker. Every decision-making process produces a final choice, which may or may not prompt action. Decision-making can be regarded as a problem-solving activity yielding a solution deemed to be optimal, or at least satisfactory. It is therefore a process which can be more or less rational or irrational and can be based on explicit or tacit knowledge and beliefs. Tacit knowledge is often used to fill the gaps in complex decision-making processes.[3] Usually, both of these types of knowledge, tacit and explicit, are used together in the decision-making process (Stanton,. Bonjean; Roelich, 2021).

Fig 1: Research Conceptual Framework



Theoretical Framework

Technology Acceptance Theory (TAT)

Davis, Bagozzi, and Warshaw (1989) came up with the TAT model in a bid to explain the user's acceptance and intention in the use of technology. TAT looks at a technology perceived ease of use and usefulness. The perceived usefulness of a technology is the belief by the user that the technology will improve his or her on job performance. The perceived ease of use looks at how easily the user can learn to use the new system or the technology (Gefen et al.,2003). According to the model, if the new technology ease of use is achieved it is likely to positively lead to perceived usefulness. There are external variables like the environment that can affect the perceived ease of use and usefulness.

This theory is often used when researching on information technologies and its main emphasis is on the two perceptive factors. Liu and Arnett (2000) looked at the important factors affecting the developing of a website based on this model. Gefen et al. (2003) used both TAT and rust and came up with a more evolved model that could be used to explain the online behaviors of customers. Parlou (2003) suggests the use of thee-commerce acceptance model on online customers that uses survey and experiment techniques. Horst, Kutts chreuter and Guttering (2007) did a follow up study that examined if it was prudent for the Netherlands government to use-government to serve its people like in other nations. The study considered TAT factors, faith, perceived risk and public experiences. The findings of the study showed that the public trusted the government and resonated with information technology. The empirical study further revealed that TAT is not only useful for examination of information technology but it also useful for examining the acceptance of intention behavior related to information technology and further explains the behavior issues faced by online users of technology(Liu and Arnett, 2000; Gefen et al., 2003).

Empirical Studies

Oluwaseun, et al. (2024) explored the integration of AI-driven technologies into business analytics to enhance decision-making across various industries. By leveraging predictive and prescriptive analytics, AI enables organizations to not only analyse historical data but also forecast future trends, allowing for more informed, proactive strategies. Machine learning plays a pivotal role in automating data-driven decisions, offering real-time insights that help businesses respond quickly to changing market dynamics. This automation significantly reduces manual intervention, increases efficiency, and enhances the accuracy of predictions. The paper further discusses the integration of AI with Business Intelligence (BI) tools to deliver deeper insights from complex datasets in real time. These insights empower companies to optimize enterprise resources, improve supply chain management, and drive operational excellence. Case studies from AI-driven analytics within Systems, Applications, and Products in Data Processing (SAP) environments highlight the practical applications of AI in real-world business contexts, demonstrating its impact on decision-making and overall performance. The paper concludes with best practices for implementing AI in business analytics, focusing on data quality, system integration, and workforce readiness to embrace AI-enabled decision-making frameworks. The findings underscore the potential of AI as a game-changer in modern business landscapes, fostering smarter, faster, and more effective decision-making processes.

Kumar, et al. (2024) explored the role of AI in enhancing decision-making quality, efficiency, and accuracy. By employing a mixed-methods approach, the study examines both the benefits and challenges associated with AI-driven decision-making. Primary data will be collected through interviews and surveys with industry professionals and AI experts, while secondary data will be sourced from existing literature and case studies. The findings are expected to highlight significant improvements in data analysis capabilities and decision-making speed due to AI, alongside identifying key challenges such as data privacy concerns, ethical considerations, and the dependency on high-quality data and computational resources. Additionally, the research will offer practical recommendations for organizations aiming to integrate AI into their decision-making processes effectively. These best practices will address both technical and ethical aspects, ensuring a balanced approach to AI implementation. The study aims to provide valuable insights for business leaders, policymakers, and academics, contributing to a deeper understanding of AI's impact on modern decision-making and offering guidance on navigating the complexities of AI integration.

Abayomi, Toluwalase and Patience (2024) explored the transformative role of predictive analytics in enhancing strategic decision-making and business performance. It delves into the components of predictive analytics, including data mining, machine learning, and statistical techniques. It highlights its historical evolution and technological enablers like big data platforms, cloud computing, and AI. The paper examines how predictive analytics improves profitability, efficiency, and market share by providing actionable insights from raw data. It also discusses emerging trends such as advancements in AI, the Internet of Things (IoT), and real-time analytics while addressing associated risks like data privacy and ethical considerations. The conclusion underscores the necessity of adopting predictive analytics for sustainable growth and competitive advantage in today's data-driven business environment.

Varun, et al. (2024) delved into the integration and impact of AI-driven predictive analytics systems within these domains. Through qualitative and quantitative analysis, the research assesses the deployment of AI-powered predictive analytics for enhancing business forecasting and decision-making capabilities. Results demonstrate improved accuracy in predictions, faster decision cycles, and enhanced strategic insights. However, challenges related to data quality and interpretability of AI-driven models also surface. These findings underscore the evolving role of AI in augmenting predictive analytics and decision-making processes in business contexts. The discussion explores future directions to address issues of model transparency and trust as AI adoption accelerates.

Sunil, (2024) examined the impact of AI-driven predictive analytics on employee retention strategies in Human Resource Management (HRM). By integrating Artificial Intelligence (AI) and Machine Learning (ML), organizations can forecast employee turnover, personalize career development, and create targeted interventions for at-risk employees. This study outlines the current applications, benefits, and challenges of AI in HRM and explains how predictive analytics can identify patterns in employee behavior to predict turnover risks. Through case studies, this paper highlights successful implementations of AI-driven retention strategies and specific tools. It also addresses ethical and privacy concerns, emphasizing transparency and fairness. Future trends and the long-term benefits of AI in HRM, such as improved employee satisfaction and reduced turnover costs, are discussed. This paper explores future trends and prospects by, considering the evolving role of AI in strategic HR planning and potential technological advancements. The long-term benefits for organizations adopting these technologies include improved employee satisfaction, reduced turnover costs, and a more engaged and stable workforce. This research underscores the critical relevance of employee retention, the innovative potential of AI and ML in HRM, and the significant impact these technologies have on organizational success.

Onyenahazi and Antwi, (2024) examined the opportunities and risks that AI presents to the investment process, focusing on how machine learning, natural language processing, and predictive analytics are reshaping asset management, portfolio optimization, and risk assessment. By leveraging AI algorithms, financial institutions can process vast amounts of data more efficiently, identify market trends, and make more informed decisions, potentially leading to enhanced returns and competitive advantages. However, the integration of AI also introduces certain risks, including algorithmic biases, cybersecurity vulnerabilities, and the potential for over-reliance on automated systems. The study investigates the balance between human expertise and AI-driven models, highlighting the challenges of transparency and interpretability in AI-based decisions. Through a combination of case studies and data analysis, this research assesses the effectiveness of AI in improving decision-making accuracy while addressing the regulatory and ethical concerns that arise from its use in the financial sector. The findings reveal that while AI offers numerous benefits for optimizing investment strategies, it is crucial for institutions to maintain robust oversight and ensure that AI systems are used complementarily with human judgment. As AI continues to evolve, understanding its impact on financial decision-making processes will be vital for institutions aiming to navigate the complexities of modern financial markets.

Nwangwu, & Nwangwu, (2023) looked at how women working in Anambra states deposit money banks' organizational sustainability in relation to work-life balance. The study looked at how the work atmosphere, employee assistance, flexible scheduling, and leave policies affected the performance of female employees. Review of pertinent theoretical and empirical literatures. The study's foundation was Border Theory. Data were gathered for the study from both primary and secondary sources. The study's sample included 953 women from selected deposit money institutions.92% of the 873 copies of the questionnaires that were properly completed and submitted were returned. Utilizing NOVA, hypotheses were evaluated. According to the data, the leave policy has a considerable positive impact on the organizational sustainability of female employees at deposit money institutions in the state of Anambra. Flexible scheduling significantly improves the organizational sustainability of female employees in Anambra state's deposit money banks. According on the findings, the study made this recommendation. It is advisable to promote a dynamic and consistent leave policy because studies show that it lowers employee churn. Compressed work weeks and other forms of flexible scheduling are essential for more effective and efficient service delivery. Organization management should sit down with the employee to discuss how and when to get the best service possible from them in order to improve service delivery.

METHODOLOGY

Research Design

This study employed the survey research design approach, gathering data from the population of interest using a structured questionnaire.

Population of the Study.

The population of this study was drawn from the management staff in the lubricant firms in Anambra state, which is a total of 281 management staff of thirteen lubricant firms within three senatorial zones in Anambra state

Table 3.1: Population Distribution of the selected lubricant firms

S\No	Names of Manufacturing Firms	Location	Mgt cadre
1	A-Z OIL	Nnewi	30
2	Seahourse oil	Ozubulu	17
3	Jezco oil	Ekwulobia	20
4	Whiz oil	Awka	26
5	Chiben oil	Onitsha	15
6	Ibeto oil	Nnewi	35
7	Visa oil	Nnewi	15
8	Dozzy oil	Atani	27
9	Envoy Oil	Onitsta	21
10	Lopa Oil	Onitsha	15
11	KM Oil	Ogbaru	17
12	Abbnox oil	Onitsha	20
13	Hariz oil	Oba	23
	Total Population		**281**

Source: Human Resource Department of the lubricant firms

Sampling Techniques and Procedures

The study used convenience sampling technique in selecting the sample size of the study based on convenience and easy accessibility to the respondents.

Source of Data

The data collected were mainly through Primary Source of Data and secondary sources of data collection. The questionnaire was one of the main sources of primary data used in this investigation.

Method of Data Analysis

Based on information gathered from the sample, inferential statistics were utilized to draw conclusions and generalize about the traits of populations. At the 0.05% level of significance, correlation analysis was used to examine the hypotheses. A method used to determine the relationship between the dependent variable and one or more explanatory factors while analyzing the relationship between two is the correlation coefficient.

PRESENTATION AND ANALYSIS OF DATA

Distributions of Questionnaire

Table 4.1.1 Information on Distribution of Questionnaire

s/n	Options	No of Respondents	Percentage %
1	Questionnaire Distributed	281	100%
2	Questionnaire Returned	273	97%
3	Questionnaire Completed	269	95%
4	Questionnaire Not Duly Completed	3	1%
5	Questionnaire Missing	1	0.3%

Source: Field Survey, 2024

Table 4.1 showed that a total number of two hundred and eighty-one (281) copies of questionnaire were distributed to the respondents, two hundred and seventy-three (273) copies which represented 97% were returned, two hundred and sixty-nine (269) which represent 95% where completed and three (3) copies which represented 1% were not duly completed by the respondents, while one (1) copy which represented only 0.36% of the total questionnaire were missing. Hence, the analyses for this study were based on the two hundred and sixty-nine (269) copies which represented 85% of the sample population.

Test Of Hypotheses

$H0_1$: Machine learning has no significant effect on decision support system on supply chain management of lubricant firms in Anambra state

$H0_2$: Neural networks has no significant effect on creative decision skill on supply chain management of lubricant firms in Anambra state

$H0_3$: Deep learning has no significant effect on analytical decision skill on supply chain management of lubricant firms in Anambra state

Hypothesis one

$H0_1$: Machine learning has no significant effect on decision support system on supply chain management of lubricant firms in Anambra state

Correlations

						MCHL	DSS
Spearman's rho	MCHL	Correlation Coefficient				1.000	.492**
		Sig. (2-tailed)				.	.000
		N				269	269
		Bootstrap[b]	Bias			.000	.001
			Std. Error			.000	.055
			BCa 95% Confidence Interval		Lower	.	.377
					Upper	.	.613
	DSS	Correlation Coefficient				.492**	1.000
		Sig. (2-tailed)				.000	.
		N				269	269
		Bootstrap[b]	Bias			.001	.000
			Std. Error			.055	.000
			BCa 95% Confidence Interval		Lower	.377	.
					Upper	.613	.

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

b. Unless otherwise noted, bootstrap results are based on 269 bootstrap samples

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	MCHL - DSS	.21561	1.57581	.09608	.40478	.52645	2.244	268	.006

Table 1a indicates the relationship between the independent variable machine learning and the dependent variable decision support system. At a 0.05 level of significant, 95% confidence level interval ranges between .613 and .526 at the upper case, and also .377 and .404 at the lower case, with a 2 tailed test of sample distribution showing the critical area in a distribution. The spearman correlation coefficient shows a value of 49% which shows a high correlation coefficient between the dependent and independent variable. This further portrays the high goodness of fit of the model

Model 1= $\mathbf{DSS = \beta_o + \beta_1 MCHL + \mu}$

Table 1 indicates the difference in mean value (.21561) and standard deviation (1.57581) for the extent of relationship that existed between the variables included in the group. The single group variables in model one of the hypotheses are represented by DSS & MICHL (Decision Support System & Machine Learning).

However, the paired sample t-test showed that Machine Learning level increased significantly when decision support system practice is adhering to. A t-test value of Machine Learning is said to be significantly high when it is above or equal to 2 (t-value > 2), but when the t-value is less than 2 (t-value < 2), it is concluded that the perceived outcome within the paired sample has no significant relationship. In conclusion to this result, the t-value was obtained at 2.244 which is significantly high. The study therefore concluded that there is a significantly positive relationship between Decision Support System & Machine Learning of lubricant industry in Anambra State

Decision Rule: Accept the null hypothesis if the p-value is greater than 0.05, otherwise, reject.

Decision: We reject the null hypothesis, since the p-value is 0.000** which is less than the critical value 0.05, this study reveals that Machine learning has significant effect on decision support system on supply chain management of lubricant firms in Anambra state.

$H0_2$: Neural networks has no significant effect on creative decision skill on supply chain management of lubricant firms in Anambra state

Correlations

					NEN	CDS
Spearman's rho	NEN	Correlation Coefficient			1.000	.534**
		Sig. (2-tailed)			.	.000
		N			269	269
		Bootstrap[c]	Bias		.000	.000
			Std. Error		.000	.066
			BCa 95% Confidence Interval	Lower	.	.309
				Upper	.	.463
	CDS	Correlation Coefficient			.534**	1.000
		Sig. (2-tailed)			.000	.
		N			269	269
		Bootstrap[c]	Bias		.000	.000
			Std. Error		.066	.000
			BCa 95% Confidence Interval	Lower	.309	.
				Upper	.463	.

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

c. Unless otherwise noted, bootstrap results are based on 269 bootstrap samples

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference Lower	95% Confidence Interval of the Difference Upper			
Pair 1	NEN - CDS	.91822	1.53832	.09379	.73355	1.10288	9.790	268	.000

Table 2 indicates the relationship between the independent variable Neural Networks (NEN) and the dependent variable Creative Decision Skill (ECS). At a 0.05 level of significant, 95% confidence level interval ranging between 0. .463 and 1.102 at the upper case, and also 0.309 and 0.733 at the lower case, with a 2 tailed test of sample distribution showing the critical area in a distribution. The spearman correlation coefficient shows a value of 0.53%, which shows a high correlation coefficient between the dependent and independent variable. This further portrays the high goodness of fit of the model

Model 2= $\mathbf{CDS = \beta_o + \beta_1 NEN + \mu}$

Table 2 indicates the difference in mean value (.91822) and standard deviation (1.53832) for the extent of relationship that existed between the variables included in the group. The single group variables in model two of the hypotheses are represented by CDS & NEN (Creative Decision Skill and Neural Network).

However, the paired sample t-test showed that creative decision skill level increased significantly when the perceived Neural Network was adopted. A t-test value of Neural Network is said to be significantly high when it is above or equal 2 (t-value > 2.00), but when the t-value is less than 2.00 (t-value < 2.00), it is concluded that the Neural Network within the paired sample has no significant relationship. In conclusion to this result, the t-value was obtained at 9.790 which is significant high. The study therefore concluded that there is a significantly high positive relationship between Creative Decision Skill and Neural Network of lubricant industry in Anambra State

Decision Rule: Accept the null hypothesis if the p-value is greater than 0.05, otherwise, reject.

Decision: We reject the null hypothesis, since the p-value is 0.000** which is less than the critical value 0.05, this study reveals that Neural networks has significant effect on creative decision skill on supply chain management of lubricant firms in Anambra state

Hypothesis Three

$H0_3$: Deep learning has no significant effect on analytical decision skill on supply chain management of lubricant firms in Anambra state

Correlations

					DEPL	ADS
Spearman's rho	DEPL	Correlation Coefficient			1.000	.620
		Sig. (2-tailed)			.	.000
		N			269	269
		Bootstrap[c]	Bias		.000	-.003
			Std. Error		.000	.061
			BCa 95% Confidence Interval	Lower	.	.448
				Upper	.	.594
	ADS	Correlation Coefficient			.620	1.000
		Sig. (2-tailed)			.000	.
		N			269	269
		Bootstrap[c]	Bias		-.003	.000
			Std. Error		.061	.000
			BCa 95% Confidence Interval	Lower	.448	.
				Upper	.594	.

c. Unless otherwise noted, bootstrap results are based on 269 bootstrap samples

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference: Lower	95% Confidence Interval of the Difference: Upper			
Pair 1	DEPL - ADS	.56877	2.10364	.12826	.32130	.41625	4.434	268	.000

Table 3 indicates the relationship between the independent variable Deep Learning (DEPL) and the dependent variable Analytical Decision Skill (ADS). At a 0.05 level of significant, 95% confidence level interval ranging between 0.594 and 0.416 at the upper case, and also 0.448 and 0.321 at the lower case, with a 2 tailed test of sample distribution showing the critical area in a distribution. The spearman correlation coefficient shows a value of 62% which shows a high correlation coefficient between the dependent and independent variable. This further portrays the high goodness of fit of the model

Model 3= $\quad$ **$ADS = \beta_o + \beta_1 DEPL + \mu$**

Table 3 indicates the difference in mean value (.56877) and standard deviation (2.10364) for the extent of relationship that existed between the variables included in the group. The single group variables in model two of the hypotheses are represented by ADS & DEPL (Analytical Decision Skill and Deep Learning).

However, the paired sample t-test showed that analytical decision skill level increased significantly when the effective Deep Learning was adopted. A t-test value of analytical decision skill is said to be significantly high when it is above or equal to 2 (t-value > 2.00), but when the t-value is less than 2.00 (t-value < 2.00), it is concluded that the perceived outcome within the paired sample has no significant relationship. In conclusion to this result, the t-value was obtained at 4.434 which is significant high. The study therefore concluded that there is significantly high positive relationship between Analytical Decision Skill and Deep Learning of lubricant industry in Anambra State

Decision Rule: Accept the null hypothesis if the p-value is greater than 0.05, otherwise, reject.

Decision: We reject the null hypothesis, since the p-value is 0.000^{**} which is less than the critical value 0.05, this study reveals that Deep learning has significant effect on analytical decision skill on supply chain management of lubricant firms in Anambra state

DISCUSSION OF FINDINGS

Machine Learning and Decision Support System

The study found that Machine learning has significant effect on decision support system on supply chain management of lubricant firms in Anambra state. A machine learning-based decision support system (DSS) can help lubricant firms make more informed and accurate decisions by analyzing large amounts of data, identifying patterns and trends, and predicting future outcomes. For example, a DSS could use machine learning algorithms to analyze historical sales data, weather patterns, and demographic information to predict future demand for lubricants in different regions. Based on this information, the DSS could recommend optimal inventory levels and production schedules, reducing costs and waste while improving customer satisfaction. The study is in line with the study of Oluwaseun, et al. (2024), Kumar, et al. (2024), Abayomi, Toluwalase and Patience (2024) who found a significant positive effect decision support system. This finding underscore the fact that Machine learning transformative role has advance the decision support system of lubricant firms.

Neural Networks and Creative Decision Skill

The study found that neural networks have significant effect on creative decision skill on supply chain management of lubricant firms in Anambra state**.** Neural networks, a subset of machine learning algorithms, can also enhance creative decision-making skills by exploring complex data sets and generating novel solutions. For example, a neural network could be trained on data from lubricant formulation experiments, allowing it to identify patterns and relationships that may not be apparent to human experts. Based on this analysis, the neural network could suggest new lubricant formulations or manufacturing processes that improve performance or reduce costs. By combining human creativity and expertise with the computational power of neural networks, lubricant firms can make faster, more innovative decisions that drive competitive advantage. The findings is in line with the study of Varun, et al. (2024), Sunil, (2024), Onyenahazi and Antwi, (2024), Faten, et al. (2024). Who found significant postive effect between neural networks and creative decision skill. Thus, this study underscores the transformative role of neural network in advancing creative decision skill within lubricant firms in Anambra State.

Deep Learning and Analytical Decision Skill

The study found that Deep learning has significant effect on analytical decision skill on supply chain management of lubricant firms in Anambra State. Deep learning, a subset of machine learning, can further enhance analytical decision skills by extracting insights from large, unstructured datasets. For example, lubricant firms can use deep learning to analyze customer feedback, social media data, and sensor data from production equipment. By identifying patterns and relationships in this data, deep learning algorithms can provide insights into customer preferences, product quality, and operational efficiency. These insights can then be used to guide data-driven decisions, such as product development, marketing strategies, and process improvements. By leveraging deep learning, lubricant firms can make more informed decisions that drive innovation and growth. The findings is in line with the study of Revenio, (2024), El Khatib and Al Falasi, (2021) and Abayomi, Toluwalase and Patience (2024), who found a positive significant effect between deep learning and analytical decision skill in lubricant firms. Thus, this study underscores the transformative role of deep learning in advancing analytical decision skill within lubricant firms in Anambra State.

Summary of Findings

Based on the review of related literature, analysis and interpretation of data and general observations, the following are the major findings of the study:

i. Machine learning has significant effect on decision support system on supply chain management of lubricant firms in Anambra state (T=2.244, P=0.006)
ii. Neural networks has significant effect on creative decision skill on supply chain management of lubricant firms in Anambra state (T=9.790, P=0.009)
iii. Deep learning has significant effect on analytical decision skill on supply chain management of lubricant firms in Anambra state, (T=4.434, P=0.000)

CONCLUSION

In conclusion, AI-powered predictive analytics represents a powerful tool for lubricant firms in Anambra State to enhance decision-making and optimize supply chain management. By leveraging the power of data and advanced analytics, firms can gain a deeper understanding of market trends, customer preferences, and operational inefficiencies, leading to improved efficiency, profitability, and competitiveness. However, the adoption of AI-based technologies requires careful planning, strategic thinking, and a commitment to ongoing learning and improvement. The implementation of AI-powered predictive analytics can significantly improve decision-making in supply chain management for lubricant firms in Anambra State, Nigeria. However, successful implementation of AI-powered predictive analytics requires strong data management, technical expertise, and cultural change within the organization. Lubricant firms in Anambra State must invest in the necessary infrastructure, human resources, and training to realize the full benefits of this technology.

RECOMMENDATION

The following recommendation were made;

i. High-quality data is essential for effective machine learning. Firms should prioritize data collection, storage, and analysis.
ii. Technical expertise is critical for implementing and optimizing neural network algorithms. Firms should consider hiring experts or providing training to existing staff.
iii. Develop a clear data strategy: Firms should develop a clear strategy for deep learning data to drive decision-making and improve operations of lubricant firms

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