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Impact of Predictive Analytics of Big Data in Supply Chain Management on Decision-Making

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ABSTRACT

The beginning of information technology has led to a burst of data in every sector of operation. Handling huge volume of data to mine useful information to support decision making is one of the current sources of competitive advantage for organizations. However, preceding research literature on predictive analytics has attributed a lack of direct causal influence on predictive analytics in a manner that support Supply Chain Management in utility companies' performance. This is as a result of huge data posing great challenges to practitioners when incorporating it into their complex decision making which adds business value. The purpose of this study was to introduce predictive analytics in supply chain management framework that enhances decision making in Kenya Power and lighting Company in Kenya. The study was guided by the following research objectives; to assess the existing predictive analytics in Supply Chain Management, to analyse existing supply chain management systems in utility companies in Kenya and to develop an integrated predictive analytics framework for big data in supply chain management for decision making in Kenya Power and lighting Company in Kenya. This research employed the Design Science research design because one of the key outcomes of the research was framework development. The study was carried out in Kenya Power & Lighting Company in Western Region in the republic of Kenya. The target population was 10 regional finance officers, 10 regional procurement officers, 47 county stores in-charges, 47 county project supervisors and 47 county business managers totalling to 161 as the sample size. The main tools for data collection were questionnaires, interview schedules and documentary review.

Keywords : Supply Chain Management, Decision-Making

I. INTRODUCTION

Predictive Analytics is a branch of Big Data Analytics that focuses on historical data to predict future trends. In a conference paper written by Jain & Shaikh (2017), on predictive analytics, they defined it as the use of data, machine learning techniques, and statistical algorithms to identify the likelihood of future outcomes based on historical data. Seyedan & Mafakheri (2020) defined Big data in terms of volume, velocity, variety, value, and veracity data and pointed out that innovative forms of information processing enable enhanced insights, decision making, and process

On the other hand, Supply chain management (SCM) is the active management of activities to maximize customer value and achieve sustainable competitive advantage. However, SCM is not just the sum of activities along the supply chain instead, it must consider the organization, supervision, and control of all activities in the chain from an integrated and collaborative perspective aiming to provide a competitive advantage (Lourenço & Ravetti, 2018) everything from product development, sourcing, production, and logistics, as well as the information systems needed to coordinate these activities. It is related to the management of all activities along with a network of organizations to provide a good or service to final customers. The efficiency of these activities can have a great impact on customer satisfaction and cost reduction.

A Decision is a process of selecting the best course of action from several available alternatives. Everybody makes a decision either knowingly or unknowingly depending on the level of intelligence. Anna, Hendrik & Evi (2020), pointed out that strategic organizational decision-making is a vigorous process in today's complex world characterized by improbability. They further emphasized that various groups of responsible employees deal with the large amount and diversity of information, which must be acquired and interpreted correctly to infer adequate alternatives. Therefore, the decision-making process can negatively affect the key operations of an organization if a decision is wrongly deduced. This will in turn, not only affect the service delivery but also the profit-making. Also, there were no known studies that employed predictive analytics of big data in the supply chain management of Kenya Power and Lighting Company in Kenya. Hence, it was in that context that the researcher was prompted to develop an integrated predictive analytics and supply chain management framework to aid the decision-making process in KPLC.

The inauguration of Web 2.0, together with Industry 4.0, the Internet of Things (IoT), and other digital technologies introduced a good deal of attention to big data and its analysis. This research is being known globally for improving performance and also benefiting from new insights. Large information is obtained from various sources such as enterprise resource planning (ERP) systems, widespread environments in manufacturing, orders and shipment logistics, social media sources, the way the customer buys, product lifecycle operations, and others.

An International Data Corporation (IDC) prediction suggested worldwide revenues for big data and business analytics (BDA) solutions had been forecasted to reach \$189.1 billion by end of 2019, which was an increase of 12.0% over a year. A new update to the Worldwide Semiannual Big Data Analytics Spending Guide (WSBDASG) from International Data Corporation (IDC) also showed that BDA revenues will maintain this pace of growth throughout the 2018-2022 forecast with a five-year compound annual growth rate (CAGR) of 13.2%. By 2022, IDC expects worldwide BDA revenue was \$274.3 billion.

Major businessmen who acknowledge Big Data as a new paradigm are seemingly offered endless promises of business transformation and operational efficiency improvements. In Supply Chain Management (SCM) in particular, some examples have captured the attention of both practitioners and researchers, hitting the headlines of recent news. Amazon employs the idea of Big Data to monitor, track and secure 1.5 billion items in its inventory that are laying around 200 fulfilment centres around the world and then relies on predictive analytics for its 'anticipatory shipping' to predict when a customer will purchase a product, and pre-ship it to a depot close to the final destination (Ritson, 2014). Wal-Mart handles more than a million customer transactions every hour (Sanders, 2014), imports the information into databases containing more than 2.5 petabytes, and asked its suppliers to tag shipments with radio frequency identification (RFID) systems (Feng et al., 2014) that can generate 100 to 1000 times the data of conventional bar code systems. UPS's deployment of telematics in their freight segment helped in their global redesign of logistical networks (Davenport and Patil, 2012).

Recent studies on big data analytics have identified various tools and techniques to help in decision-making in the supply chain. Analyzing and interpreting results in real-time can assist enterprises in making better and faster decisions to satisfy customer requirements (Govindan et al., 2018). It will also help organizations to improve their supply chain design and management by reducing costs and mitigating risks. However, Waller and Fawcett (2013) argued that previous research did not close the gap between supply chain functional knowledge, supply chain data, and BDA techniques. to succeed in Big Data, then one should consider data as a strategic asset and not as an information asset (Varela &Tjahjono, 2014) . By doing so, organizations in SCM could realize the economic value inherent in the data and the potential to capitalize on it when combined with BDA through revenue-generating activities.

Big data is a precursor to business analytics and its uptake by firms is an indication of a move towards BDA. Even though most functions in many firms have been automated, operations in most organizations are held in isolation with minimal integration and interlinking of departmental records. This frustrates prompt decision-making since a decision-maker has to go through a bureaucratic process in quest of piecemeal information that is to help them act. This gap necessitates the development of an applied predictive analytics framework for managing information and decision-making in the supply chain & logistic department of Kenya Power Company Limited. This situation is not only limited to management functions but even operational departments like supply chain management.

II. METHODS AND MATERIAL

This section explains how the research was carried out.

A. Research Design

This research employed the Design Science research design because one of the key outcomes of the research was a framework for predictive analytics in supply chain management. Design Science entails strict process of evaluating findings which help in solving observed problems, to make research contributions, to evaluate the designs, and to communicate the results to appropriate audiences (Osterle, 2011). Osterle (2011) identified Design Science artifacts include constructs, models, methods, and instantiations (Osterle, 2011). They further recommend 7 guidelines for design science research which are Design as an artifact, Problem relevance, Design evaluation, Research contributions, Research rigor, Design as a search process and Communication of research (Hevner, March, & Ram, 2004). These principles were put to use in this study. To achieve the objectives of the study, an exploratory approach with quantitative methods was considered appropriate for primary data collection.

B. Location of Study

The study was carried out in 6 counties of the western region of Kenya Power and lighting Company in the republic of Kenya. Kenya Power and lighting

Company is a long serving government of Kenya Power Corporation that supplies Power across the country

C. Study Population

The target population was 10 regional finance officers, 10 regional procurement officers, 47 county stores in-charges, 47 county project supervisors and 47 county business managers totaling to 161 respondents (KPLC, 2019). Target population refers to the entered group of individuals, subjects, or the environment which if interest to the researcher (Oso and Onen, 2005).

D. Target Population

Table 1: Target Population Matrix

Category	Target Population
Regional Finance Officers	10
Regional Procurement Officers	10
County Store In-charges	47
County Project Officers	47
County Business Managers	47
Total	161

E. Sample Size

A sample refers to a representative of the entire population which is of interest to the researcher. (Oso and Onen 2005). The sample size of 161 respondents was selected since they are of interest and hence all of them participated in the study as postulated by Mugenda and Mugenda (2016) and appropriately distributed in Kenya Power for an in-depth interview based on their administrative and management experience in regard to the Big Data Analytics driven Supply Chain Management application and decision making in supply chain and logistics of Kenya Power Company in Kenya.

F. Sampling Technique

The sample size was 62 respondents. Regional finance and procurement officers were sampled purposively since the target population was small. County store in charge, project officers and business managers were sampled using Kothari (2004) which says that 10-30% of target population formed a sizeable sample for a study.

Therefore, the sample size was 62 respondents.

Table 2: Sample Size and Sampling Technique

Category	Target Population	Sample Size	Sampling Technique
Regional Finance Officers	10	10	Purposive
Regional Procurement Officers	10	10	Purposive
County Store In-charges	47	14	Purposive
County Project Officers	47	14	Purposive
County Business Managers	47	12	Purposive
Total	161	60	

Source: Field Data 2021

G. Instrument of Data Collection

The identified tools to be used in this study were questionnaires, interview schedules and documentary review.

H. Questionnaire

A questionnaire is an instrument used to gather data by allowing measurement for or against a particular viewpoint (Orodho, 2017). The questionnaires technique was employed because of its considerable advantages in the administration. It also presents an even stimulus potentially to large numbers of people simultaneously and provides the investigation with an easy accumulation of data. Gay (2016) maintains that questionnaires give respondents freedom to express their views or opinion and also to make suggestions. This method does not identify the exact respondent. This anonymity helps to produce straightforward answer than is possible in interview where the face-face interrogation takes place. The questionnaires comprised of both close-ended and open-ended techniques. It obtained information which was compared to documentary evidences to support the study findings where the opinion of regional finance and procurement officers was sought. The questionnaires were self-administered by the researcher on scheduled days.

I. Document Analysis

This tool was used to analyse the BDA driven SCM administrative and management records in the study branches ranging from automation records, BDA driven SCM application programmes, Databases. Policy documents in regard to BDA driven SCM adoption and many other relevant documents that were obtained from study branches.

J. Pilot Study

The pilot study was done in the Western region of KPLC by the researcher prior to the main study where five functional in-charges for ICT, design and construction, customer service, operations and maintenance and marketing were included in the sample size for the pilot study. This region was picked upon because according to KPLC annual report 2018/2019 on customer connectivity, Western region recorded the greatest number of connections yet it was ranked the best in terms of new applications. Therefore, the pilot study participants were five functional in-charges since they are only five in the region, which was the greatest number of cases needed for carrying out a statistical analysis as proposed by Mugenda&Mugenda (2009). The purpose of the pilot study was to help the researcher to be aware of the reliability and validity of the instruments.

K. Validity

Validity is a quality of measurement indicating the degree to which the measure reflects the underlying methods used in obtaining it. (Mugenda & Mugenda, 2009). The researcher intends for help to the supervisors, who are experts in research, to improve on both content and construct validity of the instrument. Adjustment on the instruments was made accordingly as per the advice. Construct validity was tested by looking at the study constructs while content validity was done by ensuring the tools speak to the topic and objectives.

L. Reliability

Mugenda & Mugenda (2009) define reliability as the degree to which a research instrument and method is likely to produce the same results after several trials. In this study Cronbach'sα alpha formula was used to determine the correlation coefficient. According to Mugenda and Mugenda (2009) a minimum correlation coefficient of 0.7 was used as an indication that an instrument is reliable, and therefore the correlation coefficient of 0.7 and above was reliable for data collection. The results Were used to compute the correlation coefficient.

Cronbach'sα alpha formula was used to determine

$$\alpha = \frac{K}{K-1}\left(1 - \frac{\sum_{i=1}^{K}\sigma_{Y_i}^2}{\sigma_X^2}\right)$$

Where σ_X^2 is the variance of the observed total test scores, and $\sigma_{Y_i}^2$ is the variance of component i for the current sample of persons? The correlation co efficiency was 0.7 respectively as out lined below.

Cronbach's alpha	Internal consistency
α ≥ 0.9	Excellent (High-Stakes testing)
0.8 ≤ α < 0.9	Good (Low-Stakes testing)
0.7 ≤ α < 0.8	Acceptable (Surveys)

$0.6 \leq \alpha < 0.7$	Questionable
$0.5 \leq \alpha < 0.6$	Poor
$\alpha < 0.5$	Unacceptable

M. Data Collection Procedure

A research permit was obtained from the National Council for Science, Technology and Innovation after acquiring an introduction letter from the School of Graduate Studies from Kibabii University and thereafter the office of the HR Learning & Development of Kenya Power Company was contacted before the start of the study. The researcher administered the questionnaires to the ICT managers and their assistants. The ICT managers and their assistants was visited in their KPLC branches and the interview conducted with them. The study assured utmost confidentiality to the respondent's information. The respondents were given about one week to fill in the questionnaires after which the filled-in questionnaires were collected.

N. Data Analysis

The data was analysed to summarize the important features and relationship of data in order to generalize and determine patterns of behaviour and necessary results. The completed questionnaires were edited for completeness and consistency before responses were processed. The data collected was analysed using the descriptive design (frequency and percentages and inferential statistics) using correlations and regression analysis. Qualitative data obtained from interviews were summarized in themes and presented in narrative form in line with the study objectives; each objective was individually analysed by descriptive and inferential statistics and interpreted according to the study findings. Data was analysed using SPSS version 24 and presented using frequencies and percentages in APA tables.

O. Ethical Consideration

The researcher ensure that all information collected from the respondents is treated as confidential. The special needs managers, officers and special needs in-charges were not being identified by their names. At the same time, the study findings were open to all interested parties with a belief that they helped improve the administration and management of supply chain and logistic department in the company. A research permit was obtained from the National Council for Science, Technology and Innovation after approval by the Kibabii University and thereafter the office of the Human Resources & Development of KPLC was done prior to the actual study.

III. RESULTS AND DISCUSSION

The section discusses results for the study.

A. Response Rate

Sixty-two (60) questionnaires were distributed to respondents and sixty (58) questionnaires were received back. The response rate is shown in the Table 4.1.

Table 4.1: Response Rate

Category	Tools issued	Tools returned	Percentage return rate
Regional Finance Officers	10	9	90.00%
Regional Procurement Officers	10	9	90.00%
County Store In-charges	14	14	100.00%
County Project Officers	14	14	100.00%
County Business Managers	12	12	100.00%
Total	60	58	96.77%

60 (96.77%) return rate was realized with only 2(3.23%) questionnaires not received. Mugenda and Mugenda (2004) asserted that a response rate of more than 50% is adequate for analysis. Babbie (2004) also asserted that a 60% return rate is good and a 70% return rate is very good. Information from the questionnaires was used for analysis. Structured questionnaires were administered; respondents were given assurance of anonymity as they were not required to disclose traceable identities hence this method partly contributed to the high response rate achieved in this study.

B. Demographic information of the respondents

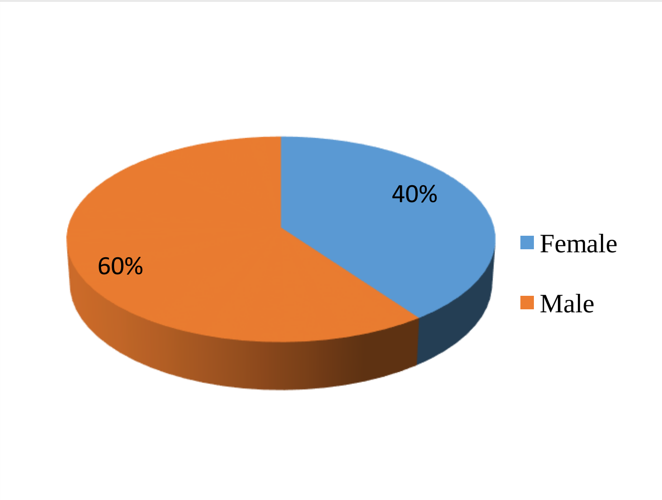

Figure 4.1: Descriptive Information on Gender

The results in figure 4.1 indicate that, 36(60%) of the total respondents were male while 124(40%) of the total respondents were female. It is therefore observed that among the respondents analysed, it seems to be dominated by males other than females.

C. Education Level

The results also revealed that 29(50%) of the respondents had a degree as the highest, 21(36.2%) of the total respondents possessed diploma's qualification, 5(8.6%) of the total respondents were having masters while 3(5.2%) had certificates. A majority 34(58.6%) of respondents were bachelors and master's holders. From the results it is evident that literacy levels are evident though only to semi literacy. This therefore made it possible for the researcher to obtain relevant responses pertaining the topic under study.

D. Experience of working in the position

Regarding duration (years) of working, 2(3.45%) of the respondents had existed for less than 2 years, 26(44.83%) had existed for between 3-5 years, 25(43.10%) had existed for between 6-10 years while 5(8.62%) had existed for over 10 years. Majority (91.38%) of the respondents had existed for below 10 years.

E. Decision making

Respondents were given statements on decision making and were required to state their level of agreement. The pertinent results are presented in Table 4.8.

Table 4.8: Pertinent Results on Decision making

Decision making	**5**	**4**	**3**	**2**	**1**	**Mean**	**Stdev**
Technology innovations have improved our supply chain operations	6.2	4.6	10.8	36.9	41.5	4.03	1.13
Technology innovations have enhanced our	4.6	4.6	12.3	38.5	40	4.05	1.07

planning capacities							
Big data analytics have improved speed of decision making	4.6	9.2	9.2	44.6	32.3	3.91	1.10
Big data analytics have improved quality of decision making	1.5	3.1	13.8	53.8	27.7	4.03	0.83
Big data analytics have improved ease of decision making	6.2	4.6	10.8	36.9	41.5	4.03	1.13
Big data analytics have shortened chain of decision making	4.6	4.6	12.3	38.5	40	4.05	1.07
Big data analytics supply chain management framework enhances decision making in an organization	6.2	4.6	10.8	36.9	41.5	4.03	1.13
Overall						4.0185714285714 3	1.06571428571429

From Table 4.8, 96(36.9%) of the sampled respondents agreed that technology innovations have improved their supply chain operations while (41.5%) strongly agreed with a mean of 4.03 and standard deviation of 1.13 implying that there is great deviation from the mean. Majority of the respondents agreed (78.4%) that technology innovations have improved their supply chain operations.

Further, (38.5%) of the respondents agreed Technology innovations have enhanced their planning capacities while (40.0%) strongly agreed on the same with a mean of 4.05 and standard deviation of 1.07. Majority of the respondents (78.5%) agreed that technology innovations have enhanced their planning capacities.

Big data analytics have improved speed of decision making as revealed by (44.6%) of the respondents who agreed and (32.3%) who strongly agreed with a mean of 3.91 and standard deviation of 1.10. Majority of the respondents (76.9%) agreed that big data analytics have improved speed of decision making. (53.8%) of the respondents agreed that big data analytics have improved quality of decision making and (27.7%) of the respondents strongly agree with a mean of 4.03 and standard deviation of 0.83. Majority of the respondents (81.5%) agreed big data analytics have improved quality of decision making. (36.9%) of the sampled respondents agreed that Big data analytics have improved ease of decision-making while (41.5%) strongly agreed with a mean of 4.03 and standard deviation of 1.13 implying that there is great deviation from the mean. Majority of the respondents agreed (78.4%) that big data analytics have improved ease of decision making.

Further, (38.5%) of the respondents agreed that Big data analytics have shortened chain of decision-making while (40.0%) strongly agreed on the same with a mean of 4.05 and standard deviation of 1.07. Majority of the respondents (78.5%) agreed that big data analytics have shortened chain of decision making. (36.9%) of the sampled respondents agreed that Big data analytics supply chain management framework enhances decision making in an organization while (41.5%) strongly agreed with a mean of 4.03 and standard deviation of 1.13 implying that there is great deviation from the mean. Majority of the respondents agreed that big data analytics supply chain management framework enhances decision making in an organization.

F. Correlation analysis

Table 4.9: Pearson Correlation Analysis

		The existing PABDA SCMs	Existing SCMs	Decision making
The existing PABD SCM	Pearson Correlation	1		
	Sig. (2-tailed)			
	N	60		
Existing SCMs	Pearson Correlation	.094	1	
	Sig. (2-tailed)	.457		
	N	60	60	
	N	60	60	60
Decision making	Pearson Correlation	.396**	.567**	.610**
	Sig. (2-tailed)	.001	.000	.000
	N	60	60	60

*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

Linear models predict values which fall in straight line by having a constant unit of change (slope) of the dependent variable for a constant unit change of the independent variable. Linearity of the variables was tested using Pearson's product moment correlation coefficient.

G. Multiple regression of the variables regressed against decision making

Objective of this study sought to investigate variables of big data analytics. This was achieved by carrying out standard multiple regressions with the model consisting of each of the variables. The study was interested in knowing the effect of each of the variables on decision making when all these constructs were entered as a block on the model. The results of multiple linear regression analysis Were presented in Table 4.14 which contained ANOVA (goodness of fit; F Ratio, Sig Value) and model summary (R, R2, Adj R^2) results while Table 4.14 contained regression coefficient (Unstandardized & standardized), t-value and Sig. value results. The study sought to determine the model summary in order to determine the overall percentage change in the decision making that was explained by the variables which was explained using R^2. The results in Table 4.15 present R, R2, Adj $R^{2,}$ F ratio and Sig. value.

Table 4.14: Model Summary and ANOVA

Model Summary				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**
1	.726[a]	.526	.495	.44109
a. Predictors: (Constant), existing predictive analytics in Supply Chain Management, existing supply chain management systems.				

ANOVA[a]						
Model		**Sum of Squares**	**Df**	**Mean Square**	**F**	**Sig.**
1	Regression	12.977	1	3.244	16.675	.000[b]
	Residual	11.674	59	.195		
	Total	24.651	60			
a. Dependent Variable: Decision making						
b. Predictors: (Constant), existing predictive analytics in Supply Chain Management, existing supply chain management systems,						

The results from the model summary in Table 4.14 give us information on the overall summary of the model. From R square, it can be deduced that all the variables account for 52.6% variance in decision making (R square =.526, P=0.000) implying that 47.4% of the variance in decision making is accounted for by other variables not captured in this model.

In order to assess the significance of the model, simply whether the study model is a better significant predictor of the decision making rather than using mean score which is considered as a guess, the study resorted to F Ratio. From the findings, the F value is more than one, as indicated by a value of 16.675, which means that enhancement as a result of model fitting is much larger than the model errors/inaccuracies that Were not used in the model (F (4,64) =16.675, P=0.000). This implies the variables are significant predictor of decision making. The presented in Table 4.15 shows unstandardized coefficients, standardized coefficients, t statistic and significant values.

Table 4.15: Coefficients on effect of Constructs of Variables on decision making

Model	Unstandardized Coefficients		Standardized Coefficients	T	Sig.
	B	Std. Error	Beta		
(Constant)	1.616	.545		2.965	.004
Existing Supply Chain Management	.270	.100	.253	2.690	.009
Existing predictive analytics in supply chain management systems	.258	.105	.302	2.462	.017

a. Dependent Variable: Decision making

All the variables had significant effect on the decision making. If the variables are held at zero or them absent, the decision-making variables would be significantly at 1.616, p=0.004. It was revealed that existing supply chain management systems had largest unique significant contribution to the model with B=.270, p=.009 suggesting that controlling of other variables in the model, a unit change in existing supply chain management systems would result to significant change in decision making by 0.270 in the same direction as a result of greater existing supply chain management systems. Therefore, the first hypothesis was rejected since $\beta_1 \neq 0$ and P value <0.05.

The second beta coefficient was 0.258, which is coefficient value for existing predictive analytics in Supply Chain Management. This value is significant (B=.258, p=.017) and also positive. This means that existing predictive analytics in Supply Chain Management has the strongest unique contribution to explaining the decision-making variables, when the variance explained by all other variables in the model is controlled. This implies that a unit change in existing predictive analytics in Supply Chain Management would result to change in decision making by 0.258 in the same direction. Therefore, the second hypothesis was rejected since $\beta_2 \neq 0$ and P value <0.05.

A regression of the predictor variables against decision making established the multiple linear regression models as indicated in Table 4.15:

Decision making =1.616 + 0.270X$_1$+0.258X$_2$.

Framework Development

The framework developed by the study is as indicated in the figure 1.

A. Framework Construct

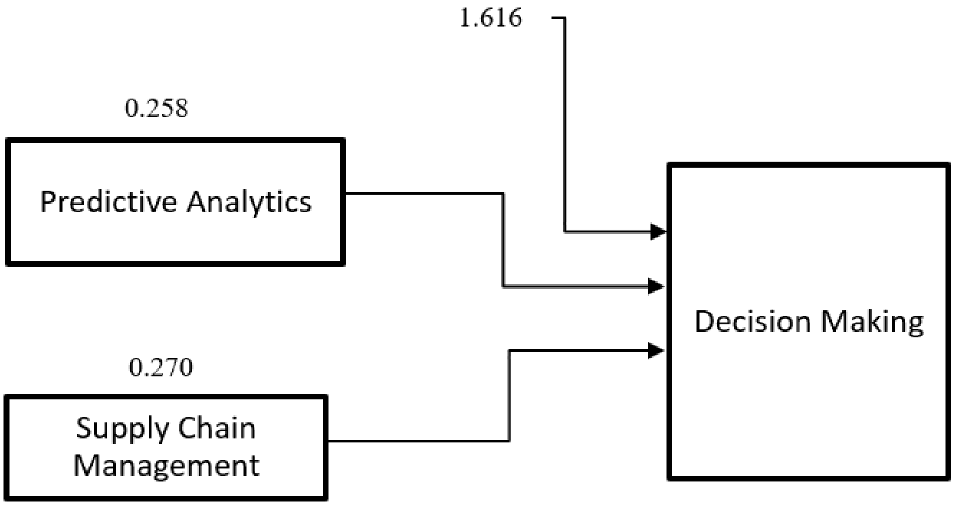

Figure 1. A developed Framework of Predictive Analytics for SCM

Fig 1 Is a framework of predictive analytics in supply chain management showing the relationship between predictive analytics and supply chain system against decision making through the expression Y = a+bX$_1$+cX$_2$. The variables Y, X$_1$ and X$_2$ are decision making, existing supply chain management and predictive analytics respectively.

B. Framework Empirical Validation

DM = Decision Making, X_1 = Predictive Analytics, X_2 = Supply Chain Management.

From the expression, $Y = aX + b$ where X and Y Are

Independent and Dependent variables respectively, while a, b are constants. This study had three variables; DM, X_1 and X_2. Therefore, the expression according to the study is;

$$DM = 1.616 + 0.258X_1 + 0.270X_2.$$

Assumptions;

Predictive Analytics can either be there or not, thus $X_1 = 0$ or 1

Also Supply Chain can either be there or not, thus $X_2 = 0$ or 1

$$\text{Suppose } X_1 = X_2 = 0,$$

$$DM = 1.616.$$

Now, when $X_1=0$ and $X_2=1$

$$DM = 1.616 + 0.258(0) + 0.270(1)$$

$$= 1.874$$

Now, when both X_1 and X_2 are present or equals to 1,

$$DM = 1.616 + 0.258(0) + 0.270(1)$$

$$= 2.144$$

It can be seen that Decision Making with Predictive Analytics is greater than Decision making without predictive analytics.

i.e 2.144 > 1.874.

Hence, predictive analytics has enhanced decision making.

From the evaluation above, predictive analytics has a positive influence on decision making which is one of the objectives of the study.

IV. CONCLUSION

The study assessed the effect of predictive analytics of big data in supply chain management on decision making in Kenya Power and Lighting Company. The study determined the framework that integrates the predictive analytics and supply chain systems to enhance decision making in Kenya power. The study showed from the framework that decision making as a variable was increase with the injection of predictive analytics. This is clearly indicated in the empirical analysis, which established that predictive analytics has a positive influence on decision making.

V. SUGGESTION FOR FURTHER STUDY

The study determined the influence of predictive analytics in supply chain management on decision making. However, the research only concentrated on one of the three branches of Big Data Analytics which is predictive analytics in supply chain management. Thus, future research can be conducted on the other two; descriptive and prescriptive analytics in relation to supply chain management to establish their relationship on a common platform.

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