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Factors Effecting the Supply Chain Performance in Automotive Industry

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Abstract

The market for supply chain analytics is expected to develop at a CAGR of 17.3 percent from 2019 to 2024, more than doubling in size. This data demonstrates how supply chain organizations understand the advantages of being able to forecast what will happen in the future with a decent degree of accuracy. Google, Netflix, and Amazon are among the main corporations that use predictive analytics. According to Gartner research, organizations that use predictive supply chains have a good return on investment. Furthermore, owing to more precise demand forecasting, they may reduce inventory by 20-30%. Predictive analytics may help remove a lot of the guesswork from planning and decision-making. Supply chain predictive analytics, as opposed to historical analytics, helps supply chain management to foresee and plan. Supply chain leaders may use this data to address supply chain difficulties, cut costs, and enhance service levels all at the same time. Predictive analytics approaches enable businesses to uncover hidden patterns and trends in their data, allowing them to better analyze market trends, identify demand and set suitable pricing strategies.

Keywords: Supply chain, original equipment manufacturers (OEMs), Big Data and Predictive Analytics (PDA), SC Visibility and SC Performance,

Introduction

The supply chain management (SCM) notion was created first in the engineering sector. The primary obvious footprint of SCM was seen in the “Just in time” (JIT) transport system in the automobile industry, especially in Toyota (Shingo, 1988). Meanwhile, the system intended to regularize the supplies in this automobile firm at right time, and the major objective of the SCM was to reduce the inventories and smooth supplies. Furthermore, the long-term association and working relationship with suppliers could develop the class and lessen the cost of production in the firms (Deming, 1988).

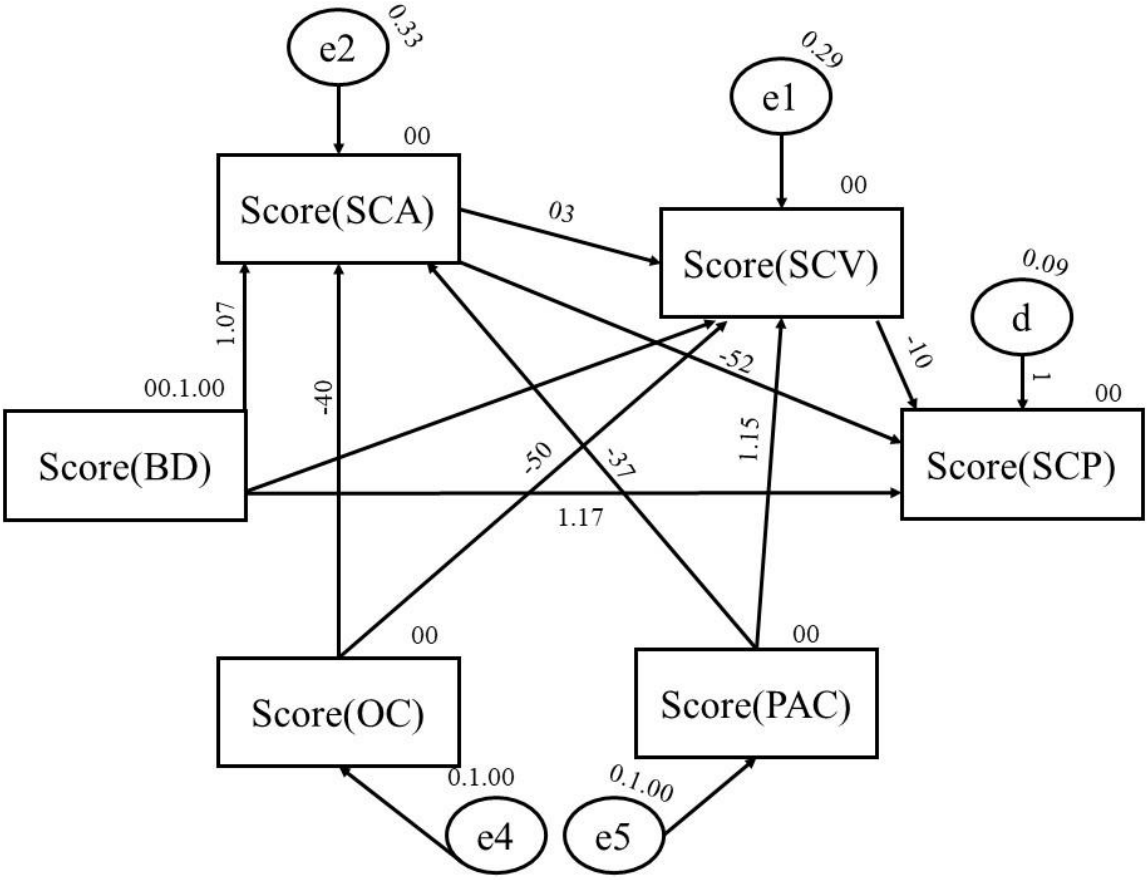
The automotive industry is passing through a transition. The traditional supply chain management, which has been used for decades and is still being used in the present day, has failed to meet the needs of the automotive industry for developing innovative products, reducing costs, and increasing productivity. This is because of the changes brought about in this industry by product development and manufacturing activities. Many industries that form part of the automotive value chain like original equipment manufacturers (OEMs), suppliers, and distributors need big data and predictive techniques to increase their overall performance efficiency. In reality, the base of competition in this industry has been changing for a few decades, although the style and innovation in the product remained the ground of competition with challenging parts of customization and order in time (Wieland, 2021).

Literature Review

Raman et al. (2018) figure out the effectiveness of the supply chain industry of big data to effectively and efficiently introduce new value by ensuring operational excellence, promoting cost-saving steps, accelerating customer loyalty and visibility in real-time, and reducing the distance between SCM as well as demand management, thus affecting the implementation of large data technology. The study demonstrates a positive association between big data and supply chain management. Jebel et al. 2018 articulate the effect on an organization's sustainable business annual average Big Data growth rate and predictive analysis by formulating a theoretical model. The results show the BDPA's organizational ability can support organizations to reinforce their environmental, social, and economic sustainability. The study revealed that BDPA has a direct relationship to the economic, social, and environmental performance of the industrial business.

Speech act theory makes it possible to understand and predict the new developments and changes in Supply Chain Management. Since it is a profoundly, coherent, and multidimensional theory that can be applied to any situation or context; it opens new perspectives for understanding Supply Chain Management phenomena from a different point of view. Ordines et al. (2017) present a novel approach for leveraging archival data to advance marketing objectives by developing a vibrant understanding of customer sentiments. This study used the qualitative analysis technique of identifying discourse patterns based on text mining for measuring sentiment in a social media setting. The big data is accumulated by user-generated word of mouth. Drawing on the speech act theory, this study expanded the understanding of customer sentiments beyond the use of positive and negative words; and instead, offered a fine granule analysis of implicit and explicit words used by consumers to express sentiments in text. Directions provided for future research chiefly recommend the use of data mining-based sentiment analysis of video and/or audio data. Additionally, it is also recommended to advance knowledge on negation sentiments by translating the differential impact of each negative assertion in customer reviews. In doing so, a deeper understanding of consumer sentiments expressed in the user-generated content can be achieved with the application of marketing analytics on customer reviews big data chunks.

In the management of the supply chain, different factors are involved which must be addressed to understand the facts and pay attention to various factors. One of these factors that have been studied in recent years is speech act theory. This theory has been used to analyze different aspects of the SCM process and show its impact on performance. For example, it was noticed that certain types of promises can positively affect performance, while others negatively affect it. These findings suggest that managers should be aware of which type of acts they perform during a supply chain transaction to boost efficiency or use it as a way for additional communication between partners.



Methodology and Data Analysis

In the past, supply chain management has been a highly dependent component of manufacturing. But with new technologies and innovations, such as Big Data and Predictive Analytics (PDA), supply chains are receiving a huge boost in their performance. PDA is an integration of three different areas: decision trees (analyzing historical data to predict upcoming outcomes), machine learning algorithms (learning from predictive analytics and factors that influence it), and business intelligence (analyzing historical data at different periods). Therefore, my paper aims to study how big data and predictive analytics help improve supply chain performance by disrupting processes in the automotive industry.

Predictive analytics on supply chain performance in the automotive industry. Some important variables affecting supply chain optimization among them are world consumption rate and gross profit margin with maintaining quality and increasing production efficiency. Various techniques and tools have been used to analyze data in both manual and automated ways to find out what are the best practices in this area. The expert estimated that the automotive industry will lead innovation in AI, which means the market share of automobiles will continue to rise, improving forecast accuracy improves supply chain analysis. The new demand curve shows a greater focus on the sustainable development of production organizations, which leads to new problems for effective forecasting. According to the McKinsey Global Institute Report on the future of the auto industry, the forecast accuracy improvements will directly contribute to reducing supply chain costs, while sustainability factors also influence car industry development.

In the foreseeable future, the automotive industry's innovation in artificial intelligence will be its most significant feature, leading to a favorable increase in market share. Competitors with a lower market share should be especially concerned with their inability to offer new features that can entice potential customers.

Data Analysis

Big Data (BD) with Predictive Analytics is considered and the innovative tool used in modern supply chain automotive management systems. The objective is to search the relationships between the impact of BD and Predictive C_{AB} SC Performance using moderation and mediation approaches. To study this problem, a survey was conducted amongst an auto manufacturer's customers regarding their predictions about supplier performance; as well as the relationship of SC management in the automotive industry. A questionnaire was sent to 302 automobile industries and our respondents were Director managers, Assistance managers, and supervisors, hence we got 220 valid responses for analysis.

Summary Model AC+SCV+SCP				
Model	S	S^2	$(S_{adj})^2$	Std. The error in the Estimate
1	.734[a]	.539	.534	.24498
a. Predictors: (Constant), SCP, PAC				

Table 01: Moderation Analysis of SC Visibility and SC Performance [Data interpreter from SPSS Software].

Table 01 shows moderation analysis of SC Visibility and SC Performance in the presence of C_{AB} as a Moderator and the 3rd column R^2 gives the percentage of the relation between the designed estimated structure and dependent variable from of Zero to hundred percentage scales. As we all known considering the S^2 .32 < r^- < .51, considerable effective structure is not strengthened; if the S^2 is.51< r^- < .72, impact structure is moderate; and if the S^2 value is > 0.71, the effect size is high. Table 4.1 shows that the value of S^2 is .539 revealing 53.9% in SCP. The design is taken as acceptable due to the value of F that can compare the fits of different models and significance is observed below .005.

Coefficient						
Designed Parameters		Un-standard Coefficients		Std. Coefficients	T	F
		B	Std. Error	Beta		
1	(Constant)	.685	.135		5.056	.000
	PAC	.981	.064	.882	15.320	.000
	SCP	.380	.066	.330	5.727	.000
a. Dependent Variable: SCV						

Table 02: Shows the Major Impact between PAC and SCP because the p is weaker than .005 [Data interpreter from SPSS Software].

Table 02 shows the major impact between PAC and SCP because the p is less weak .005. Even though SCV and SCP also give a positive impact p- value show a significant relationship, the p-value of variables showed a significant relationship between SCV and SCP. The moderation term explains that there is a moderately significant association among these variables. According to the obtained results, it is analyzed that SCV and SCP are being moderated by AC. The unstandardized coefficients for this study were (0.685, 0.981, and 0.380), respectively. These coefficients show a positive relationship of SCV and SC visibility and supply chain working, but it is not significantly different from zero or one. The standardized coefficient for the model where absorptive capacity as a moderator is included was (.882), this means that each unit increase in absorptive capacity is associated with a .882 percent increase in supply chain performance.

Similarly, above table shows that the value of R^2 is .539 revealing that 53% variation in PAC and SCP. The model is considered a fit due to the value of F that can compare the fits of different models and significance which is observed below .005.

Association of Agility and Performance of SC in the Presence of C_{AB} as a Moderator

The current study presents the impact of absorptive capacity as a mild coefficient between SC agility and SC performance.

Model Summary AC+SCA+SCP				
Model	R^	R^2	$(S_{adj})^2$	Std. The error of the evaluation
1	.188[a]	.036	.026	.98672990
a. Predictors: (Constant), (PAC), (SCP)				

Table 03: Moderation Analysis of Agility and Performance of the SC in the presence of Absorptive Capacity as a Moderator [Data interpreter from SPSS Software].

Table 03 shows moderation analysis of Agility and Performance of the SC in the presence of Absorptive Capacity as a Moderator and the 3[rd] column R^2 gives the relationship of structure and the value varying of 0-100% scale. Consider the R^2 .31 < r < .52, the structure will be considered as low; the value R^2 is.52< r<.71, the impact will be moderate; and R^2 is >.71, the effect size is taken high. Similarly, the table shows that the value of R^2 is .035 revealing a 35% variation in SCP. The model is taken fit due to F that can compare the fits of different models and significance which observed below .005.

Coefficients[a]						
Model		Unstd Coefficients		Std Coefficients	t	F
		B	Std. Error	Beta		
1	(Constant)	2.826E-15	.067		2.04	.000
	(SCP)	.234	.083	.234	2.813	.005
	(AC)	.150	.083	.150	1.795	.074
a. Dependent Variable: (SCA)						

Table 04: A Relationship between AC and SCP [Data interpreter from SPSS Software].

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Table 04 shows a significant relationship between AC and SCP. The t-value of 2.04 and p>0.1 of variables showed a significance relationship between AC and SCP. Moderation term analyze that there is a moderately significant association among variables. According to the obtained results, it was analyzed that SCA and SCP are being moderated by AC. The standardized coefficients are used to effectively compare the association between the 2 independents. The standardized coefficient is correlated between a dependent divided and an independent variable by its standard error. In this case, it is the correlation between agility and performance of the SC in the presence of absorptive capacity as a moderator. The unstandardized coefficients are used to interpret how much of an effect a variable has on a certain outcome variable. The unstandardized coefficients for SC agility and SC performance in the presence of absorptive capacity are 0.150 and 0.234, respectively.

Similarly, above table shows that the value of R^2 is .035 which revealing a 35% variation in AC and SCP. The model is considered a fit due to the value of F that can compare the fits of different models and significance which is observed below .005. This shows that there exists no major difference between these variables, which means there is no impact on each other when used independently or in conjunction with each other.

GENDER					
		F	P	VP	CP
V	Male	112	50.9	50.9	50.9
	female	108	49.1	49.1	100.0
	Total	220	100.0	100.0	

Table 05: Data Teaching Table [Data interpreter from SPSS Software].

Table 05 shows that 50.9% of the queries are male while 49.1% of the queries are female. The Column second the value of F shows the frequency which is detected in the data frequency graph while the value of P in the 3rd Column shows the Percentage of data collected from male and female. It is necessary to mention the number of influential people in data to understand the effect of results achieved for software.

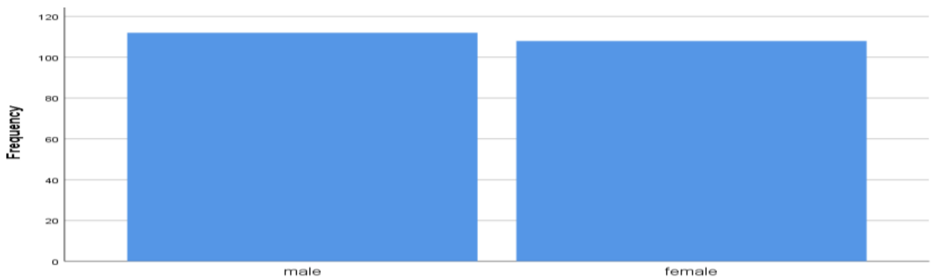

Figure 01: Data Frequency Graph. [Data interpreter from SPSS Software]

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The figure 01 interpretation the data frequency table 05 in which male and female frequencies are shown. Graph is first side demonstration of the data collection from different respondents.

What is profession of the respondent						
		F	P	VP	CP
V	Director manager	85	38.7	38.7	38.7
	Assistance manager	87	39.4	39.4	78.3
	supervisor	48	21.7	21.9	100.0
	Total	220	100.0	100.0	

Table 06: Profession of the Respondent [Data interpreter from SPSS Software].

Table 06 interpretation that 38.6% of the respondents are director manager, 39.5% are assistance manager and 21.8% of the respondents are supervisors. Column 3rd, the value of F is frequency of the respondent which gives the total number of people responding for the data while the value of P in 4th column shows the probity out of 100% of the responded.

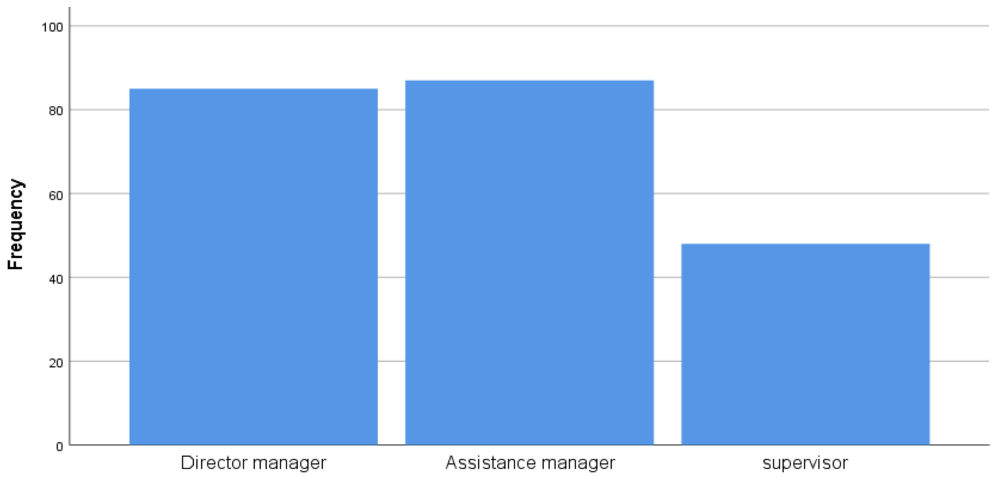

Figure 02: Frequency verses Respondent varietal data. [Data interpreter from SPSS Software].

Figure 02 interpretation the Frequency verses Respondent varietal data in which the number of director manager 85, assistance manager 87, supervisor 48

The data access to very large, unstd, or fast-moving data for examination					
		F	P	VP	CP
V	Never	93	42.3	42.3	42.3
	Rarely	74	33.6	33.6	75.9
	sometimes	18	8.2	8.2	84.1
	frequently	35	15.9	15.9	100.0
	Total	220	100.0	100.0	

Table 07: Data access for Examination [Data interpreter from SPSS Software].

Table 07 depicts that 93 respondents have given the answer in never, 74 have responses in rarely, while 18 respondents have given the answer in sometimes and 35 have responded in to frequently. Column 3rd, the value of F is frequency of the respondent which gives the total number of people responding for the data while the value of P in4th column shows the probity out of 100% of the responded.

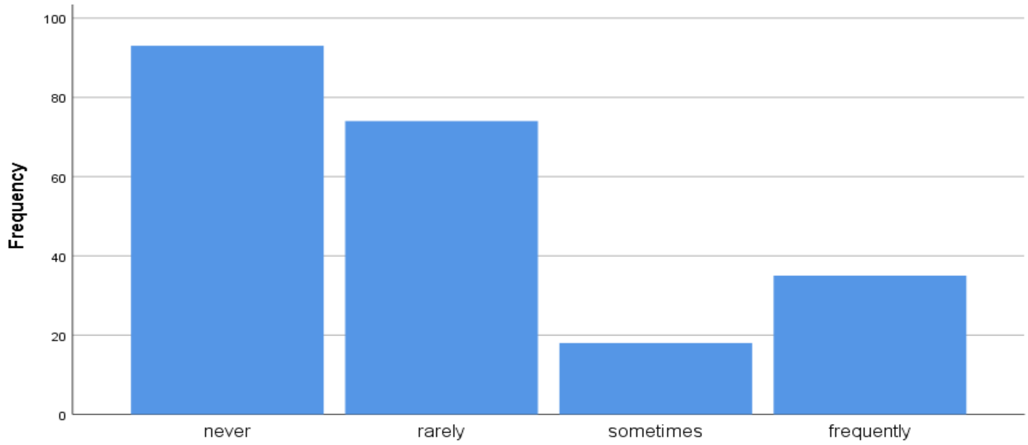

Figure 03: Frequency verses large, unstd, or fast-moving data. [Data interpreter from SPSS Software].

Figure 03 interpretation the Frequency verses large, unstd, or fast-moving data. In which the number of Never 93, rarely 74, sometimes 18, frequently 35

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Consolidate data from multiple inner sources into a data warehouse or mart for easy entry					
		F	P	VP	CP
V	never	4	1.8	1.8	1.8
	rarely	51	23.2	23.2	25.0
	sometimes	28	12.7	12.7	37.7
	frequently	120	54.5	54.5	92.3
	to a great extent	17	7.7	7.7	100.0
	Total	220	100.0	100.0	

Table 08: Consolidate data from Multiple inner sources [Data interpreter from SPSS Software].

Table 08 depicts that 51 respondents have given the answer in never, 28 have responses in rarely, while 120 respondents have given the answer in sometimes and 17 have responded in to a great extent Column 3rd, the value of F is frequency of the respondent which gives the total number of people responding for the data while the value of P in 4th column shows the probity out of 100% of the responded.

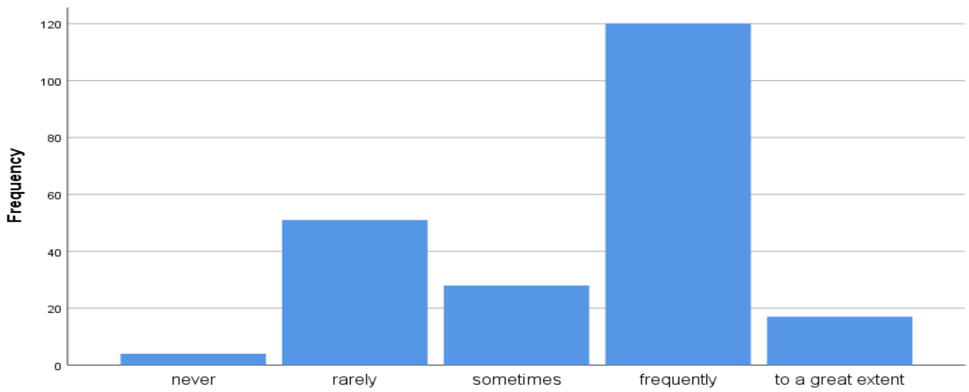

Figure 04: Frequency verses Multiple inner sources into a data warehouse [Data interpreter from SPSS Software].

Figure 04 interpretation the Frequency verses multiple inner sources into a data warehouse. In which the number of never 4, rarely 51, sometimes 28, frequently 120, to a great extent 17

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Discussion and Conclusion

The automotive industry is the second largest manufacturing sector in the United States, (Platzer, 2009), and it has seen rapid growth in its supply chain over the last decade. Whether an auto-related firm is a producer or a supplier, products must be designed, prototyped, manufactured, warehoused, and distributed to meet customers' demands. This makes agile and cohesive supply chains crucial to success in the automotive industry. To succeed in this industry, which is impacted by environmental unpredictability and quick changes, the absorptive capability is essential. This study looked at the moderating effects of organizational performance and absorptive ability, as well as the mediating effects of supply chain agility and supply chain visibility.

The results of research investigating the impact of big data on supply chain performance (SCA) were presented. Data were obtained from the automotive industry, and they were analyzed using regression analysis. Regression analysis is a common way to derive useful insights from data and is used extensively in economics, population biology, marketing, financial analysis, and many other fields. The results exposed that absorptive capacity has an affirmative and significant effect on SCP.

Big data denotes large volumes of data gathered from multiple sources including social media interactions which are analyzed using advanced computing techniques, particularly statistical analysis, and machine learning. The term has gained prominence in the last couple of years due to the growing importance of big data analytics in the fields of business, IT, and even science.

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