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# Business Analytics: Application of Supply Chain Operation Reference (SCOR) In Business Decision Making

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**Abstract**
**Purpose:** This paper aims to review the impact and importance of Business Analytics (BA) as an essential aspect of a mixture of skills that optimizes a corporation's data and performance, and as a guide to data-driven decision-making of a corporation. Next, Supply Chain Operation Reference (SCOR) in supply chain performance (SCP) will also be reviewed in this paper as it is an established supply chain improvement methodology in the manufacturing or corporations. Consequently, the author reviews the usage of BA into SCOR for decision making.
**Design/methodology/approach:** A systematic literature review was conducted on the applications of different BA approaches in managing the supply chain performance using the SCOR model. The literature review explains the BA, SCOR methodology and subsequently explains the importance of BA on SCOR to support this conceptual paper.
**Findings:** This study reviews the usage of BA into SCOR for decision making in the manufacturing industry, especially in the Malaysian semiconductor manufacturing industry.
**Research limitations/implications:** This paper only explores the application of BA on the SCOR model in the manufacturing industry.
**Practical implications:** Implications of this paper is to assist the manufacturing industry in decision making using BA and ease the application of SCOR methodology in determining its supply chain performance (SCP).
**Originality/value:** To the best of the authors' knowledge, the proposed concept of applying BA into SCOR for decision making is still unexplored. The discovery of this new concept will help the corporations or manufacturer to ease their application of SCOR.

**Keywords**: Business Analytics (BA), Supply Chain Performance (SCP), Supply Chain Operation Reference (SCOR), Key Performance Indicator (KPI)

## Introduction

Business Analytics (BA) is the best qualitative methodologies of enabling quantitative methods to derive valuable information based on data and statistical methods to boost business. BA has been applied across many fields such as health care, stock markets, medicine and forecasting to make informed business decisions. The current applications of BA emphasize predictive analytics (PA). PA is defined as a branch of analytics that optimizes the application input data, statistical combinations, and intelligence of machine learning statistics to predict the plausibility of a particular event happening and forecast future trends, and has gained attention in the forecasting markets and the manufacturing sector (Espadinha-Cruz, et al., 2021; Izagirre, et al., 2021).

In the manufacturing sector, supply chain management is evolving at a fast pace. Supply chain systems are getting more complex and integrated as manufacturers divert the production from their own country and subcontract them to other countries across the globe (Choi and Choi, 2021). By having a healthy supply chain, a country or corporation will not be indisputably challenged by any hostile competing parties, resulting in damaging the overall performance of the specific country or corporation (Lu, et al., 2021).

Malaysia is a well-known semiconductor manufacturing site. The semiconductor manufacturing export contributes 37.8% of the total exports in Malaysia, which accounts for total revenue of RM 372.67 billion. It is expected to surge in the near future due to the ongoing trade war and semiconductor shortages (MIDA, 2020b).

The application of BA into the Supply Chain Operation Reference (SCOR) methodology to determine supply chain performance (SCP) is important. It provides the stability of manufacturing firms to execute customer demand without any disruption due to technical or non-technical issues. Based on the importance of supply chain stability and its financial potential, deep-dive research on applying BA into the SCOR methodology in the Malaysian semiconductor manufacturing sector was explored.

In terms of geography, Malaysia has a significant advantage of being a neutral state that does not support any side from western or eastern powers, thus providing safety to the offshore investment (Tham, et al., 2019; Fang, 2020). Malaysia is a neutral state which is one of the added advantages to evade high technological products sale sanctions by the United States on sale to China, and by having it locally manufactured in Malaysia, these corporations can evade the sanctions (Tham, et al., 2019; Fang, 2020). In addition to that, Malaysia is located strategically along the Strait of Malacca, which is a major sea route connecting the Far East to Asia, Europe, and the Middle East, and it would be economical for these manufacturing hubs to exist as the sole manufacturing site (Ngu et al., 2020).

In terms of cost, Malaysia has the advantage of high English literacy and low labour cost, as early as back in the ’70s, which encouraged various semiconductor giants to invest in Malaysia (Eltegen et al., 2020). Not only that, different tax breaks, such as 70 to 100 percent tax breaks, for any new International Semiconductor Manufacturing base for the first ten years, will be an added advantage for Malaysia to serve as a global manufacturing site (MIDA, 2020a).

This conceptual paper will give much attention to applying SCOR, an established supply chain methodology, with business decision-making based on the importance and future studies of BA in SCOR. This paper begins with the literature review of BA and SCOR followed by the importance of BA and suggestions for the future, which will be described in the last two sections of this paper.

## Literature Review

### Business Analytics

BA combines techniques, technologies, and applications used to scrutinize a corporation's data and performance to transpire data-driven decision-making analytics for future direction and investment plans (Bayrak, 2015; Kristoffersen et al., 2021). Data-driven corporations will manage their data as assets and actively look for ways to turn it into a competitive advantage against competitors (Bawack and Ahmad, 2021). In this new era of big data, data-driven analytics is the choice for many major industries such as manufacturing, IT, marketing, and logistics. They are eager to understand consumer spending and their behaviors to maximize potential profits (Bibri and Krogstie, 2021). There are three types of analytics that drive business decisions: descriptive, prescriptive, and predictive analytics.

Descriptive analytics interprets historical sets of data for a specific timeframe to identify valuable trends and patterns. This process includes drilling down into on-hand data to explore and understand details such as the occurrence of events, the value of operations, and the failure mode (Loeb et al., 2017; Kaur et al., 2018; Ondes, 2021). In general, descriptive analytics can be understood as using historical data to provide insights to enable corporations to improve and manage their business processes.

Descriptive analytics has been used to describe COVID-19 patients in India. It is used to define and characterize all the COVID-19 patients in 2020 by breaking the data down by age, sex, and district, using the box and whisker plot (Bhatnagar et al., 2021). Descriptive analytics has been used in describing worker assistance systems in the manufacturing industry by explaining step by step the process of using on-hand data for verification. This systematic strategy gives extra added value advantages for the manufacturing corporations to improve the well-being of the workers (Mark et al., 2021).

Descriptive analytics has been used in influencing electrical vehicle adoption, whereby the author signifies population, the number of charging stations available, the number of subsidies, and the breakdown of electric vehicle owners by education background (Foley et al., 2020). In the healthcare industry, descriptive analytics was used to identify Patient Turnover and its relations to the Patient-to-Nurse ratio, whereby it enables healthcare service agents to deliver safe and well-grounded care when the market request is soaring while preventing overstaffing, hence translating to headcount optimization (Musy et al., 2020).

Prescriptive analytics, on the other hand, is defined as the application of testing various techniques (mathematically or computationally) to determine the outcome that will yield the best result in a given scenario to improve the performance of a corporation (Arismendy et al., 2021; Lana et al., 2021). It studies the opportunity of a decision, correlation of the decisions, influences that impact these decisions, and finally, comes out with an outcome that uses all inputs to deduce the best solution in real-time (Arismendy et al., 2021).

Prescriptive analytics has been used in competitive manufacturing, a field of high-value manufacturing, in Sweden to identify types of challenges related to internal and external environments when operating in a high-cost environment (Mirzaei et al., 2021). In Egypt, it has also been applied to help design buildings that focus on optimizing energy efficiency for commercial buildings and green buildings rating systems (Elakkad and Ismaeel, 2021). Prescriptive analytics was also applied in the cement industry in Nigeria to identify the cause and effect of cement quality on the building of data centers and its implications in the health, safety, and environmental inspections of neighborhoods (Nwankwo and Ukhurebor, 2020).

Prescriptive analytics was also used in public-sector infrastructure planning decision making to shape the availability of public infrastructure in Amsterdam, Netherlands (Brandt et al., 2021). In the healthcare industry, prescriptive analytics was used for medical decision making in precision medicine, and it is considerably prominent in replacing old school medical decision making (Mosavi and Santos, 2020).

The third type of analytics, predictive analytics (PA), is defined as the branch of analytics that scrutinize the application of input data, statistical combinations and Machine Learning statistics on predicting the probability of a particular event happening, forecast future trends or outcomes utilizing on-hand data with the final objective of improving the performance of the corporation (Kumar and Garg, 2018; Davenport, et al., 2020; Espadinha-Cruz, et al., 2021; Izagirre, et al., 2021). Corporations have shown to effectively interpret big data (BD) using PA by capturing the relationship among factors to assess risk with a particular set of conditions and by assigning scores, weightage or parameters to deduce the future trends or outcomes (de Medeiros, et al., 2020; Brynjolfsson, et al., 2021). The latest application of PA in the management of supply chain was explained by Sholeh et al. (2021) on the application of construction supply chain where SCOR has been utilized into the BA in decision making in material usage, vendor selection and payment duration of the construction supply chain. The following section will further discuss SCOR and its process hierarchy.

The main features and characteristics of the three BA types can be explained in short as below (Chehbi-Gamoura, et al., 2019):

Descriptive analytics:
Data + Model (Descriptive statistics) = Description of the past (1)

Predictive analytics:
Data + Model (Predictive statistics) = Prediction oriented to the future (2)

Prescriptive analytics:
Data (structured and unstructured) + Model (complex models from various domains) + Rules = Prediction + Decision + Recommendation of the action + Advice (3)

**Supply Chain Operations Reference (SCOR)**

Supply Chain Operations Reference (SCOR) was first tabulated in 1997 by Supply Chain Council (SCC), a non-profit corporation for industry experts to discuss emerging global supply chain management issues. The primary purpose of SCC is to summarize and simplify methodology and analytical techniques and to identify benchmarking standards to help corporations improve their supply chain process.

The SCOR model is a standardized reference tool to manage supply chain under the same unified format applicable to any product, service, or industry. Since its introduction in 1997, SCOR has undergone various revisions. The current version 12, revised in 2017, has been rebranded to Association for Supply Chain Management (APICS) and is now fully rebranded into APICS Supply Chain Council (APICS, 2017). The new SCOR model consists of four major parts: performances, process, practices, and people. Performances in SCOR indicate both the overall performance and the specific performance under each process to define the strategic goal of the 'user's corporations, while process describes a standard description of the supply chain management process and their relationship. On the other hand, practices refer to the management practices as a guide to the SCOR user while using the SCOR methodology to improve their business, whilst peoples tend to describe skills in the staffing of the workforce needed to execute a smooth supply chain process.

SCOR methodology has been successfully implemented across the board in various industries and corporations to help in process optimization, waste reduction practices, and establish a standardized terminology that eases internal and external communication across corporations and fields, resulting in the improved overall process.

**SCOR Process and Hierarchy**

SCOR process consists of six primary management processes of plan, source, make, deliver, return and enable, as shown in Figure 1.

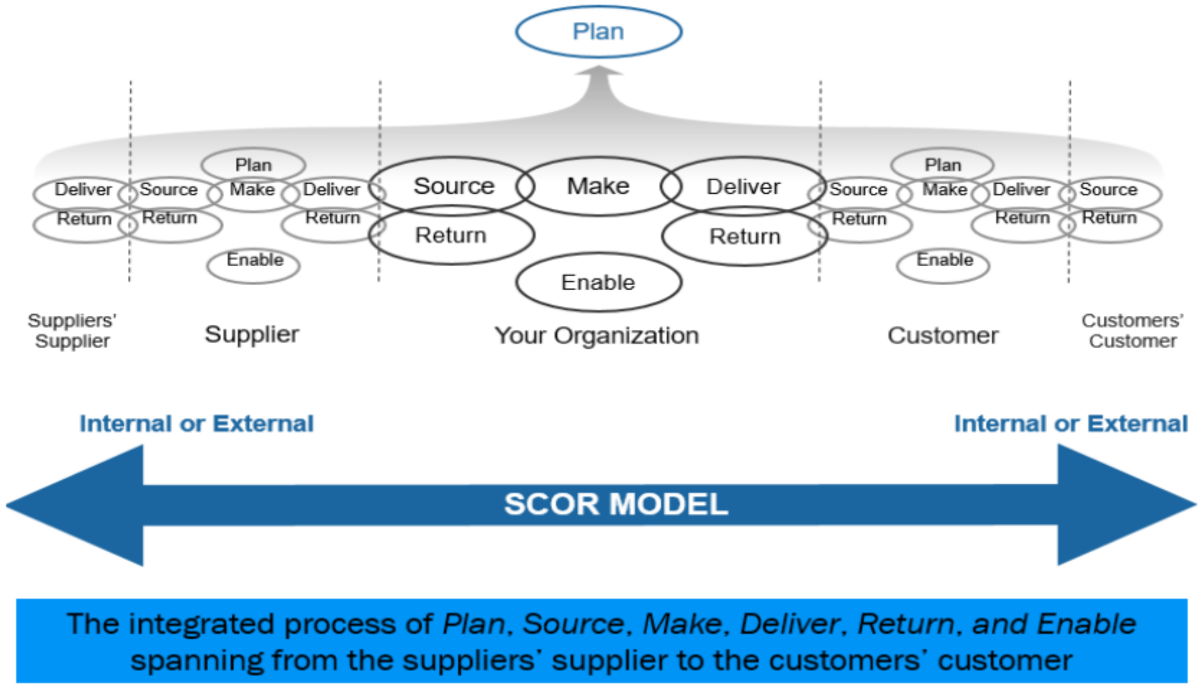


Figure 1: SCOR model with six management process (APICS, 2017)

SCOR process definitions according to the SCOR model described in Table 1 below.

Table 1: SCOR Process according to SCOR model (APICS, 2017)

| SCOR Process | Description |
|---|---|
| Plan | Coordination of supply chain resources in supply chain system to achieve optimum demand that includes requirement and identifying actions required to be executed to achieve the desired goal |
| Source | Process of ordering, delivering, receiving, transferring raw material to execute the task to bring out product and services |
| Make | Process that creates added value to the corporation, such as scheduling and manufacturing, to create a high value-added final product |
| Deliver | Process to handle order management and order fulfilments in transportation and distributions of orders to end customers |
| Return | Process that handles customer returns of a defect product from customer to the supplier of the product or to perform the maintenance activities |
| Enable | Process that facilitates the management in business rules, performance and regulatory to meet the corporation needs through interactions with other departments such as finances, facility, and legal to support the governance of planning and execution in supply chain |

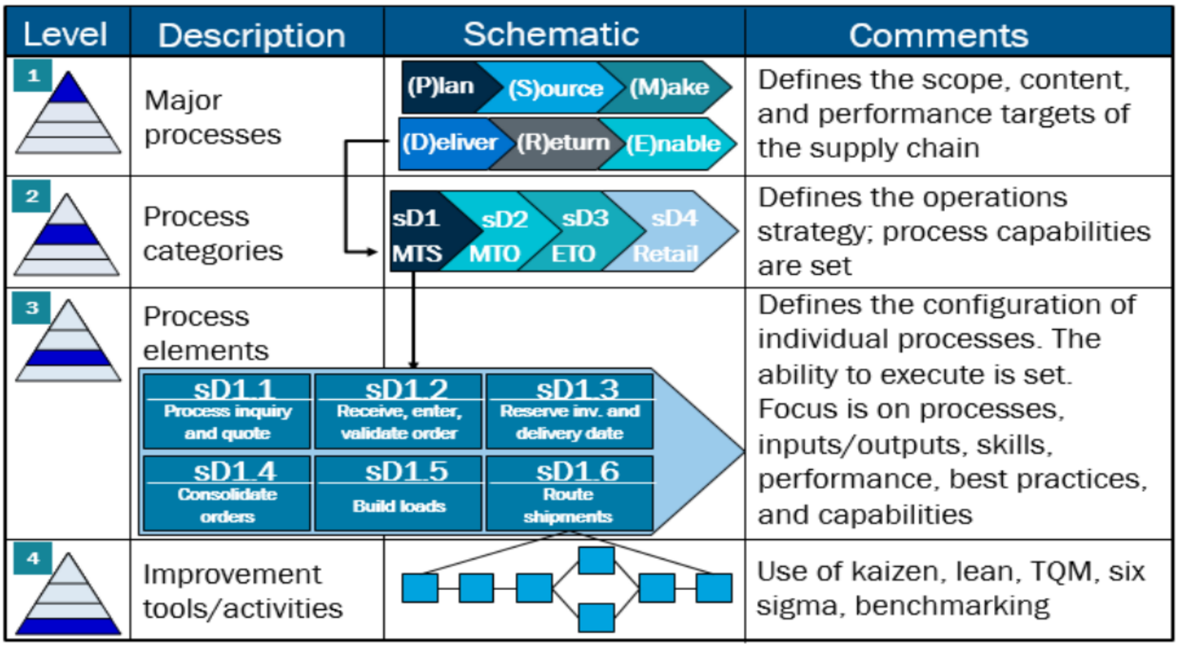

Figure 2: SCOR hierarchical structure (APICS, 2017)

Based on Figure 2, the SCOR model was designed to support the supply chain in four hierarchical levels. SCOR level one focuses on the major processes that deal with the six major processes of supply chain. The major processes are further broken down into their major process categories (i.e., plan, source, make, deliver, return and enable). On the other hand, SCOR level two, three and four explains the configuration of the capability of the process categories, elements and its improvement to be executed.

**Importance of Business Analytics on SCOR Methodology**

SCOR is divided into six main processes, comprising the performance metrics and the measurement matrices in a hierarchical structure. It has been applied in various industries and research, as it has an organized structure that simplifies its adaptability (Vlahakis, et al., 2020). The COVID-19 pandemic saw massive disruptions in the supply chain; hence, the usage of BA into the SCOR methodology to mitigate supply chain issues in SCP is very feasible and easy to use as SCOR consists of a vast number of parameters that generates a huge load of data (Chalmeta and Barqueros-Munoz, 2021).

The application of BA on the supply chain has been used to describe the process where users use historical supply chain data to predict future trends and reduce supply chain risk to the overall supply chain (Chalmeta and Barqueros-Munoz, 2021). BA on supply chain healthiness has also been used in the fields of logistics, predictive maintenance, pricing strategies, inventory management, economic instability, inflation, purchasing power, and this could help adjust the predictions to adhere to the unseen future scenarios of demand (Maheshwari, et al., 2021).

BA tools such as predictive analytics will provide a better field of view of the overall parameter on the expected results and eliminate the hassles of focusing on all SCOR parameters. Furthermore, using the BA approach will reduce the effort and time to manage the vast number of parameters proposed by the SCOR methodology. SCOR consists of various KPI's, and BA can be applied to reduce possibilities of distractions from top priorities that could potentially lead to some important KPIs being traded off (Villazon, et al., 2020; Marcano, et al., 2021).

In the future, supply chain will be the key factor in determining the performance of a country or corporation as it will determine the number of products or services produced, and hence, will directly or indirectly be translated to revenue (Al-Zabidi, et al., 2021). Hence, by having a healthy supply chain, the country or corporation will not be indisputably challenged by any hostile competing parties that will damage overall performance of this specific country or corporation (Lu, et al., 2021). Furthermore, the SCOR model has a very significant impact on supply chain performance. It is a very established platform on the effectiveness of implementation as it consists of many parameters and needs to be scrutinized from time to time (Riahi, et al., 2021). Thus, by implementing BA into SCOR, SCOR will be better analyzed and scrutinized.

Application of BA on SCOR can optimize supplier plans and forecast the availability of raw materials, which will help reduce excess inventory cost and track defective parts on incoming material (Katsaliaki, et al., 2021). Besides that, applying BA in SCOR methodology will help in cost reduction in streamlining supply chain performance. It will further enable corporations to understand risk in supply chain performance, create a lean supply chain, and gain significant return on investment (Darvazeh, et al., 2020).

Table 2 list some examples of BA on the supply chain. Since SCOR is derived from supply chain, it further justifies the usage of BA on SCOR methodology. It is worthwhile to apply BA to SCOR, especially in the Malaysian semiconductor manufacturing industry, which will be explained in the next section on suggestions for future research.

Table 2: Relevant Business Analytics literature review and its recent application on supply chain

| Author and Year | Sector/ Industry/ Domain | Key Takeaways |
|---|---|---|
| Lamba and Singh (2017) | Unstructured data and predictive analytics in various levels of analytics in Supply chain Management | The authors highlighted the usage of unstructured data (text, audio, video and social media) with BA (predictive analytics) |
| Nguyen et al. (2017); Chehbi-Gamoura et al. (2019) | Few levels of analytics in Supply Chain Management | The authors highlighted the new classification model, but the study is focused on the question: Where BA is applied in supply chain management and its variables |
| Mathu and Phetla (2018) | Major packaged fast food supply chain in South Africa | The authors highlighted that the SCOR KPI’s support the Just In Time (JIT) methodology where BA is applied to eliminates waste in manufacturing |
| Novar et al. (2018) | Manufacturing/ Rice Manufacturer supply chain in Indonesia | The authors highlighted that the SCOR KPI’s using BA helps in providing data ranking interpretation of sourcing performance and the overall rice supply chain performance |

| | | |
|---|---|---|
| Sholeh et al. (2021) | Construction supply Chain in Indonesian (Mix concrete and steel) | The authors highlighted that the SCOR KPI's is used with Analytic Hierarchy Process (AHP) methodology for quantitative analytics |

**Conclusion and Suggestions for Future Research**

In summary, business analytics and its application in business decision making can be applied to SCOR as SCOR has an established data parameter tabulation. Using analytics for future studies through prescriptive and predictive methodology can be applied to gain competitive advantage. Application of BA approach will effectively reduce effort and time to manage the vast number of parameters as review by SCOR. SCOR consists of various KPI's, and BA can be applied to reduce possibilities of distractions from top priorities of the vast amount of data generated that could potentially lead to some important KPI to be traded off during analysis (Villazon, et al., 2020; Marcano, et al., 2021).

Malaysia semiconductor manufacturing industry plays a vital role in maintaining a healthy global supply chain. The application of BA and SCOR methodology in Malaysia's semiconductor manufacturing industry will be crucial for future researchers.

This paper's significance and perspective are to propose the idea to assist the Malaysian manufacturing industry in decision making using BA and ease applying SCOR methodology in determining its supply chain performance (SCP). Enabling BA into SCOR will enable Malaysia manufacturing firms to better stabilize customers' demand without any disruption of incoming raw materials due to technical or non-technical issues. The limitations of BA into SCOR are that SCOR is very limited to a data-centric environment. It will not function to its full potential in an environment that does not generate a vast amount of data.

**Conflict of Interest**

This discourse paper review is a nonprofit review paper that does not acquire any specific stake from the merchant, general public, or nonprofit corporation.

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