Impact of Predictive Analytics on Supply Chain Management

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Abstract This paper explores and analyses the impact of Predictive Analytics on Supply Chain Management. Predictive Analytics is expanding, and many organisations are utilising this technology for improved benefits and profits. The supply chain consists of different sectors which can inculcate this technology for overall optimization. This research uses primary and secondary data to illustrate the aim and objective of the research. The literature review gives an in-depth overview of the concepts of Big Data and Predictive Analytics (PA) in Supply Chain Management. The outcomes of this research have led to the conclusions that PA plays a critical role in supply chain function optimization and can provide important insights for better decision making. They also point to the improvement of Supply Chain processes through the effective and efficient application of Predictive Analytics, resulting in improved performance, optimised procedures, and increased profits. In addition to that, many technologies can aid new start-ups and entrepreneurs towards success with their effective implementation and give rise to new business models to even larger organizations. This research can thus aid other organisations to understand the importance of PA and how well it can aid in strategic planning and execution and gain an advantage over their competitors.

1 INTRODUCTION

The advancement of newer and upcoming technologies such as Machine Learning (ML), Cloud Computing, Artificial Intelligence (AI), Data Analytics (DA), Internet of Things (IoT), etc. has created immense levels of discussions and arguments regarding their growth, advantages and risks (Tuptuk, Hailes, 2018). Everyday immense amount of data is created which is then stored, processed, managed, and then

used to interpret and visualize information to improve organisational capabilities. To increase consumer base, productivity and innovation, it is crucial for data systems to advance their analysing capacity which require mathematical, statistical and computational methods (Esmaeilbeigi et.al., 2020). Thus, Big Data has been proved to add a lot of value and enhance any firm's competitive advantage (Tiwari, Wee & Daryanto, 2018). It is a high-performance strategy where data can be converted into useful insights which can lead to great success. Thus, BD has many opportunities for new and upcoming entrepreneurs as well (Sedkaoui, 2019). Predictive Analytics (PA) has been proving to be one of the most used and vital components in all fields. This analysis rests on statistical approaches along with other more recently developed tools of data mining. The purpose of these strategies is to anticipate predictions and projections about the organization's operations in the future. (Ouahilal et al., 2016).

Data analytics enables businesses to make better decisions and implement them when it is most advantageous to the company, its end consumers, and partners (Ouahilal et al., 2016). Companies can improve their internal processes, enrich their products and services around data, and also market and supply their data to external services, thus monetizing themselves (Weiner et. Al., 2020). According on the depth of study, data analytics can be classified into four types: descriptive analytics, diagnostic analytics, predictive analytics, and prescriptive analytics. This research aids in understanding the use of predictive analytics to help people make better decisions. PA helps to understand the following for any organisation-

- What is predicted?
- What can be done about it?

These major concerns for any organisation can be dealt with the help of PA. The open-ended nature of these questions leads to a vast array of industries using this technology in all processes (Siegel, 2016). Supply chain managers are using PA in forecasting demands, inventory and stock management, distribution and logistics processes, pricing strategies, predictive maintenance, etc. Some predictions even state that the market is supposed to grow at a CARG of 17.3% from 2019 to 2024. Thus, supply chain professionals can predict challenges and improve costs and service levels (Riverlogic, 2021). Although large firms are the primary users of predictive analytics, there are various other industries and organisations where predictive analytics technologies can be beneficial to decision makers (Attaran and Attaran, 2019). Many companies have started extracting potential out of their strategic business models using big data, which is giving rise to big-data business models (BDBMs). These BDBMs are not only just assets or resources, but are strategic aspects that aid in organizational value creation and capture. But there are some companies like Facebook who have been facing challenges when it comes to BDBMs due to their privacy issues (Weiner et al., 2020). It is thus wise for organizations to plan and deploy BDBMs and other technologies strategically to avoid consequences. This research thus aims to understand the impact of PA on SCM. It will also help to understand its applications in all sectors of supply chains.

As there has been very limited research done on the actual impact of PA on all sectors of Supply Chain Management, this paper will help to gain an overall insight into it. The topic of supply chain management predictive analytics offers a promising path for revolutionising supply chain management, and also an intriguing array of research prospects (Schoenherr and Speier-Pero, 2015). Predictive analytics enables businesses to transition from a retrospective and intuitive decision-making process to one that is proactive and data-driven.

It can be said that big data technology is still in its infancy, which combined with the initial financial costs and a lack of expertise about how to deploy it, makes it difficult to accept in the supply chain business (Raman et al., 2018). Hence, the limited amount of material and database available can be considered to be limitations to the study.

2 LITERATURE REVIEW

2.1 What is Big Data Analytics?

In recent times there has been tremendous growth of big data. There have emerged many breakthroughs that manage large transfer of data which is collected from different sources. These can be found in petabytes and beyond in structured, semi-structured, and unstructured formats (Acharjya and Ahmed, 2016). The utilisation of tools and methods for analysing and processing variables and patterns from excessive amounts of data is required when using Big Data as a resource (Riahi and Riahi, 2018). The range of applications of BD in SCM is quite vast and helps in consumer behaviour, demand and supply forecasting, trend analysis, etc. Accurate marketing along with forecasting models have helped understand customer needs and expectations. With the rise in information technologies and improved computational strategies, BDA can provide precise predictions in risk assessments, improve SC efficiency, assess consumer needs and performance (Seyedan and Mafakheri, 2020). Using data analytics and artificial intelligence, a supply chain unicorn, Convoy, based in Seattle, US, managed to reduce carbon emissions by providing real-time data to match shippers and carriers efficiently (Fortune, 2021).

Data analysis is revising the business and corporate world, allowing organisations to better their performance and overall processes, providing them with a competitive advantage (Sharma and Bhat, 2014). Data driven business models are proving to have 5-6 percent higher productivity. For example, publishers are able to target their demographics based on data in their digital distribution channels which then can be

sold which enable more efficient targeting. Moreover, around 71 percent of banking firms have also seen to gain competitive advantage with the use of data (Brownlow, et.al., 2015). Radio-frequency identification (RFID), tracking devices, various sensory information and other technologies are used in the supply chain business to collect massive volumes of data (Zhong et al., 2015). Data management can be said to be extracting and storing data along with preparing and retrieving it for analysis, using algorithms and accompanying technologies. Whereas analytics can be said to be the techniques used for analysing and extracting insights from enormous amounts of data. Thus, big data analytics can be considered to be a subordinate process inside the wider process of retrieving insights from enormous amounts of data (Gandomi and Haider, 2015). Everyday huge amounts of data are generated, and Data Scientists are striving hard to come up with solutions to manage, control and analyse this data to for the benefit of companies and organisations (Nasser and Tariq, 2015). Creating new found ventures using data and novel digital technologies, many entrepreneurs can reap benefits and become successful (Chae and Goh, 2020). In supply chain management, processes can be enhanced, and supply chain sectors can better track and trace every path of goods and services and can even mitigate and avoid risks on time. Big data has the following characteristics-

Volume- Volume is the quantity of data which is generated and then stored and operated in systems. Organisations face hurdles to analyse and process data saved for many years due to lack of technological support. This can be considered to be a big benefit if companies can process this data (Ishwarappa and Anuradha 2015). As everything is now tracked and recorded every second, this massive amount of captured data cannot be processed using traditional systems. It is thus clear that the percentage of data which is generated is growing and the data that needs to be processed and analysed is decreasing resulting a blind zone (Nasser and Tariq, 2015).

Variety-Variety can be considered as the structural variability in a dataset. Thanks to technology improvements, businesses may now use a variety of organised, semi-structured, and unstructured data (Gandomi and Haider, 2015). Most data generated is of unstructured form. So, most analysts should have the knowledge to deal with different types of data to avoid complexities when it comes to analysing it (Ishwarappa and Anuradha, 2015). Structured data which is referred to as tubular data form is easy to process. Unstructured data includes images, text, videos and audio files. Semi-structured comes between the two and does not conform to any standards. Due to the development of new data management techniques and data analytics, businesses can leverage data in their business processes, which is a unique feature (Gandomi and Haider, 2015).

Velocity- Velocity is considered to be the frequency with which data is extracted, stored and then analysed. Most of the data needs to be processed and analysed in real time for good results (Riahi and Riahi, 2018). Traditional data management solutions are unable to process huge data flows in real time. In this case, big data technology can help. They enable companies to derive real-time intelligence from massive amounts of perishable data. Data from mobile devices and applications generates massive quantity of data that can be used to develop real-time,

individualised offers towards regular consumers. This data comprises essential consumer information such as geospatial location, demographics, and historical purchasing behaviours, all of which may be evaluated in real time to provide meaningful customer value (Gandomi and Haider, 2015).
Veracity-This term can be said to be the data's uncertainties, impressions, lies, and missing values. This aspect assesses the data precision and its ability to be used for analysis. The degree of correctness of the data sets that is collected in systems will decide whether the data is valuable. Many academics believe that this is Big Data's largest hurdle (Nasser and Tariq, 2015). It is thus vital to monitor and manage the quality and accuracy of the data to have the best results.
Value- Value is also considered to be a crucial aspect of Big Data. Large volume of unstructured data is collected but most of it can be useless. This data can have value if it is properly analysed and made useful (Ishwarappa and Anuradha, 2015).
All these characteristics can be considered to be current challenges faced by big data. It is vital and necessary to understand that the defining limitations are determined by the firm's size, sector, and location, and they change over time (Gandomi and Haider, 2015). Data analytics can be divided into four categories (Rajaraman, 2016), as outlined in the below sections.

2.1.1 Descriptive Analytics-

Descriptive analytics makes use of historical or past data to determine the current state of a situation. It consolidates all the gathered data from various sources and presents in analytical ways to have a better vision over the problem (Ouahilal et al., 2016). The data implications can be visualised using various charts, bar graphs, pie charts, scatter diagrams, etc. Decision makers usually make use of these visualisation techniques to analyse the data and provide with accurate solutions to optimise processes. A good example of descriptive analytics is where the population of a country can be classified based on sex, age, income, density, education, etc. (Rajaraman, 2016).

2.1.2 Diagnostic Analytics-

Diagnostic analytics determines the root cause of the problem by understand why something happened in the first place. It tries to gauge the causes and behaviours of the events (Riahi and Riahi, 2018). Diagnostic analytics help decision makers to take the correct steps after they determine the errors as it provides them with the answer to the question why it happened. An example of diagnostic analytics can be that of a plane’s engine where it sends information to operational databases and then the maintenance department can devise solutions based on the data (Funmilola and David, 2019).

2.1.3 Predictive Analytics-

Predictive analytics is one the most important types of analytics. It predicts what can happen in the future by analysing past data. It uses statistical algorithms and various machine learning techniques to determine and forecast the future steps to be taken (Ouahilal et al., 2016). It can help by processing and analysing historical data to predict patterns and behaviours which can be even days, months or years from the present. Decision makers thus make good use of predictive analytics to improve profit margins and propose accurate steps (Funmilola and David, 2019). An example of predictive analytics is in retail marketing where data from the consumers can be gathered and processed to market the correct and saleable merchandise in the stores (Rajaraman, 2016).

2.1.4 Prescriptive Analytics-

Prescriptive analytics helps to achieve the answers towards a specific goal. It provides solutions to existing problems (Rajaraman, 2016). The purpose of prescriptive analytics is to look at existing or present patterns and forecasts and make judgments based on that knowledge. The goal of prescriptive analytics is to recommend or prescribe the optimal decision possibilities based on enormous amounts of data so that companies can reap the benefits in the foreseeable future. It does so by combining the outputs of predictive analytics along with artificial intelligence, enhanced algorithms, and smart devices and systems in a probable environment that result in adaptive, automated, limited, time-sensitive, and optimal judgments (Lepeniotia et al., 2020). An example here can be that of airlines maximising profits by analysing data of past holidays, destinations, durations, etc and providing prices and seat reservations (Rajaraman, 2016).

2.2 Importance of Predictive Analytics

Predictive analytics is a part of data analytics which provides future insights based on historical trends and data. The generation of these future outcomes can be very accurate and precise, and some may even provide a foresight which is seconds, days, weeks or even years ahead. It uses many mathematical techniques along with statistical modelling, big data, machine learning and many other algorithms to predict future events. As the prediction of the future is a crucial aspect to any business, predictive analytics has been considered to be an important part of many organisations (Sumithradevi and Raja, 2019).

Predictive analytics can cope with a variety of situations. There are both continuous and discontinuous changes (Mishra and Silakari, 2012). Predictive analytics is composed of two words- predict and analyse. But it works reversely where it first analyses and then uses machine learning techniques to predict. Lead by data, predictive analytics is considered to be inductive. Creating these models can be very tricky as some might not give the correct results. Developing predictive models necessitates a lot of effort, and the outcomes are not always guaranteed to be useful (Eckerson, 2007). PA is used in supply chains, healthcare, robotics, architecture, financial and insurance industries, retail, travel, social networking and telecommunication, IT, Government and Public sectors, Oil and Gas industries, etc (Ongsulee et al., 2018). This applicability makes PA one of the most desirable and extensively used application in the current scenario.
Many artificial intelligence (AI) applications use machine learning as a way of computational learning. ML algorithms are versatile tools that can make predictions and at the same time learn from trillions of data points. Machine learning can be thought of as a modern-day version of predictive analytics. While it's critical for businesses to understand the differences between machine learning and predictive analytics, it's also crucial to understand how they're linked. Machine learning is a branch of predictive analytics (Ongsulee et al., 2018).

2.3 Predictive Analytics Process

Predictive Analytics involves many processes by which analysts usually predict future events. It has a series of tasks that occur gradually:

2.3.1 Requirement Collection

The main aim and objective of a project is defined here. The desired outcomes are discussed with the client according to their demands and requirements (Eckerson, 2007). It also defines the knowledge that will be gained after prediction of insights. For developing the proper model, specific usage of data is also discussed with the client (Kumar and Garg, 2018).

2.3.2 Data Collection

Once the specifications and requirements of the clients are met, the next stage involves acquiring data from respective datasets. Different organisations may use different datasets to gain data from consumers (Kumar and Garg, 2018). Data may be

structured, unstructured or semi-structured. Data analysts then capture the data for analysis and the time taken depends on the type.

2.3.3 Data Analysis and Massaging

For the creation of models, the data collected is extracted, cleaned and then processed (Eckerson, 2007). Here the extracted data is cleaned and made into a structured format. Sometimes the captured data may even have some errors, so it has to be tested before analysis. All the issues must be addressed beforehand as the quality of data is the most vital factor for the creation of the predictive model (Kumar and Garg, 2018).

2.3.4 Statistics and Machine Learning

There are many Machine Learning and statistical techniques which are used in PA. Regression analysis and probability theory are commonly used (Kumar and Garg, 2018). The end result and the solution needed is dependent on the approach taken and the devised technique followed (Fuentes, 2018). Statistical techniques have to be involved in the process even though they are traditional techniques compared to Machine Learning ones.

2.3.5 Predictive Modelling

At this stage a model is developed and tested on a test data set which is derived from the main dataset. If the model is successful, it is considered to be a finalist. After investigating many techniques, approaches and models, the finalists are then considered to be the promising one which will give out the best solution. Once this model is made final, it predicts accurate results based on the dataset to meet the desired project specifications (Kumar and Garg, 2018).

2.3.6 Predictions and Monitoring

Once the model starts to predict insights, it is then monitored and checked. The accuracy and quality of the results is also monitored to improve and optimize performance (Eckerson, 2007). All this can be done at the client's location and according to their requirements so that any errors or issues can be dealt with at the very moment.

This step-by-step path leads to the development of the final model which helps in predicting future insights and goals as required. The decision-making process utilizes all these processes, and all are a vital part of the whole circle from collection to final deployment in PA (Kumar and Garg, 2018).

2.4 Predictive Analytics and Supply Chain Management-

Nowadays supply chain professionals are overwhelmed with massive amounts of data across all platforms. This large amount of data needs to be processed and analysed to be made useful to benefit supply chains (Hazen et al., 2014). Predictive analytics can be a useful tool for many supply chain businesses which can help in cost effectiveness, data management, improved lead times, better forecasting which all can improve performance. Many organisations are flooded in data, with a lot attempting to gain a competitive advantage through data analysis (Davenport, 2006). The difficulties and consequences of poor data quality are becoming increasingly important to supply chain management. As the quality of data has been of immense importance in businesses, many suffer when it comes to analysing vast amount of data as the demand and capabilities of these businesses keep growing (Parssian, Sarkar, Jacob, 2004).

Predictive Analytics and Big Data Technology (BDPA) can help in leading towards value creation in the entire cycle of the supply chain. It also enhances the resilience, robustness, risk management and overall organizational performance (Gunasekaran et al., 2017). Even most practitioners have a tough time comprehending the skills that are needed to turn data into value. Despite its widespread use in the industry, many businesses are hesitant to engage in this technology because of the difficulty in identifying potential benefits. Furthermore, research on BDPA capabilities in the supply chain is scarce, necessitating a thorough examination of its capabilities so as to reap the benefits of big data. Various companies thus have to consider the organizational, human resource and many other technical challenges to improve the value and to gain better future prospects in comparison to their competitors (Arunachalam, Kumar, Kawalek, 2018). In order to absorb PA in different processes and to have a high supply chain and operational performance, the entire top management should not only gain resources, but also give all their efforts to this process by organising and investing in gathering resources (Gunasekaran et al., 2017).

So, the overall aim of the paper is to explore the impact that the use of PA has on supply chain organizations that implement it. There has been limited research done on the actual impact of PA on the overall organisational performance. So, this research will help in understanding the effect that these new technological advancements can change the way supply chains function and create outstanding results when implemented. To understand this, the use of predictive analytics in the various sectors of supply chains is necessary.

2.4.1 Procurement

Procurement has been helping organizations to reduce costs with the help of tactful contract management and also improving value propositions. Most of the operations have been digitized and organizations are now focusing on developing strategic plans of action (Ateş et al., 2018). Technology in procurement enhances relationships and skills and capabilities, achieve cost efficiency, optimise processes and increase performance. It allows for new organisational configurations and it analyses by gaining procurement and organisational integration and alignment through the management of priorities into unambiguous procurement results that are always in line with the business strategy (Biazzin, Castro-Carvalho, 2019). Massive datasets may be retrieved, aggregated, and transformed into valuable information and knowledge using BDPA, which can then be used as decision support systems to conduct deep analyses and improve operational performance, particularly in the field of smart manufacturing (Ranjan, Jayanthi, and Cyril Foropon, 2021).

Top management is responsible to align the firm's procurement policies, corporate policies and data analytics strategies to run parallel with the firm's own strategic objectives (Gunasekaran et al., 2017). Businesses must focus on the strengths of human and technological roles, which necessitates a thorough grasp of human judgement and technological capabilities to support data management and have consistent insights (Schoemaker & Tetlock, 2017).

When it comes to procurement issues, common difficulties and decisions include supply and demand management, cost and budget reduction, developing costing models, innovations in procurement, market categorization strategies and intelligence, supply chain risks, supplier management and stakeholder evaluation. To approach and solve these issues, procurement technology is required along with a vehicle for segregating data from multiple sources (e.g., ERP systems, procure-to-pay systems, contract management systems (CMS), and third-party systems and devices), processing, and presenting information to users, who then act on it (Handfield, Jeong and Choi, 2019). Statistics, graphical visualisation tools, simulation, and mathematical methods are all employed in PA. Increasing information transparency among supply chain actors can assist all stakeholders in achieving their overarching goal of enhanced stockholder value. Increased asset velocity (e.g. inventory turns) and the ability to move material swiftly through supply networks are both aided by improved access to supply chain data (Handfield, Jeong and Choi, 2019). As a result, data visibility increases reaction to demand shifts and disruptions, assisting in the management of supplier risk and performance (Handfield and Linton, 2017). Advanced analytics, risk and resilience management, sustainability, globalisation, adoption, finance, innovation, transparency, and people, will be the greatest disruptive factor in the procurement department (Handfield, Jeong and Choi, 2019).

Most innovative procurement technologies are still in their early stages of development, and only a few major companies have successfully implemented them. Real-

time spend analysis, in combination with visualisation tools and properly drafted contract inquiries, will add a new level of value (Handfield, Jeong and Choi, 2019). Spend analysis can be paired with contract expiration data to yield valuable insights. Predictive analytics and cognitive technology may be able to link pricing differentials or other elements to unexpected changes in market conditions (Handfield, Jeong and Choi, 2019). Risk analytics provide an initial stage of warning signs towards upcoming disruptions. Shorter product life cycles are associated with faster technical progress. This short-term and volatile product life-cycle has caused demand planning and procurement to be unreliable (Kuo et al., 2021).
Procurement predictive analytics tends to have an impact on many different sectors like visibility in supply chains, social media and information systems, flow of data between systems, standards of management and transmission, and cybersecurity of buyers and suppliers (Stevens and Johnson, 2016). It can thus be seen that the future is all about predicting the accurate insights and will help in success of procurement processes in supply chains (Kuo, Peng and Kuo, 2021).

2.4.2 Manufacturing

With the introduction of internet of things (IoT), asset handling and monitoring sensors, weblogs, social media posts, product and components tracking, and other technologies, manufacturing and service industries have to deal with increasingly large amounts of data in a limited amount of time. These businesses are no strangers to storing large datasets, but actionable and manageable insights from the data are frequently absent (Shukla, Tiwari, Beydoun, 2019). Predictive analytics helps to play a major role in manufacturing by improving product forecasting, performance management through various manufacturing sectors, product and service quality, operational visibility, customer preferences and purchasing patterns, real-time or current manufacturing processes and asset maintenance, product design, customer service and consulting, and many other (Govindan, Cheng, Mishra, & Shukla, 2018). Although there are numerous advantages to employing PA, its acceptance in many organisations is still in its infancy.
Making intelligent production systems that are "self-aware," "self-predict," and "self-maintain" is one of the most difficult tasks facing the manufacturing industry today. The Predictive Manufacturing System (PMS) encapsulates a variety of technologies and methodologies, including statistics, data modelling and data mining, and artificial intelligence. These tools and methods are used to transform data into useful information and give predictions about the system under study (Nikolic et al., 2017). To achieve transparency, manufacturing companies must have advanced predictive analytics, as well as IoT, data mining, networks for intelligent sensors, along with big data, to transform a large amount of collected data into useful information and gather or store it in the cloud, so it can be available for use at any given point of time and place (Nikolic et al., 2017). Industry 4.0 has cyber-physical

systems that are linked with the internet of things to create intelligent predictive systems, virtual presentation, and interfaces that can be operated from any point to support predictive manufacturing systems and organized industrial environments. The manufacturing process becomes more adaptable, and intelligent embedded devices begin to function in unison (Gunasekaran et al., 2018).
The BDPA plays a critical role in an organization's agility. By having an integrated and developed supply chain network, and collaboration among other sectors, along with giving timely and more precise information about product demand and have proper processes in place, it can aid in optimal performance (Gunasekaran et al., 2018).
Despite the steady advancement of relevant technologies for the implementation of PMS, there are still a number of difficulties to address. The creation of algorithms that can learn from and handle a variety of scenarios can be considered as a major issue that has a broad array of hurdles in PMS and also Industry 4.0 entirely (Kang, 2016). Data security in PMS is also a serious worry, as massive data is housed in virtual cloud platforms. Thus, more research is required in this field of improving storage of such massive amounts of data (Wuest et al., 2016). Moreover, top management has a critical role in the adoption of analytic tools as practical decision-making approaches in the application of PA technology. The analysts' good thinking abilities and comprehension of statistics aid in making proper conclusions and thus optimizing operations (Raut et al., 2021).

2.4.3 Logistics and Distribution

The logistics and transportation business are a blend of the networks, infrastructure, equipment, information technology, and employees required to convey a wide variety of items safely and effectively throughout the country and around the world (Stefan, 2017). Trains, aircraft, ships, and trucks are all part of an interconnected transportation network, despite the fact that they are commonly thought of as independent entities.
Data science, predictive analytics, and big data may be able to assist logistics managers in meeting internal needs and adapting to supply chain changes (Govindana et al., 2018). Access to real-time data is gaining a lot of importance in supply chain and logistics decision making. A supply chain logistics manager can efficiently substitute flow of goods and products with information flow at a significantly lower cost if they have a better awareness of inventory location and demand information. Some sort of tracking technology is now most likely generating and delivering the most beneficial, real-time supply chain data (Basole, Nowak, 2018).
BDPA can be used in inventory management, marketing, analysing consumer demands and sentiments, optimizing transport, analysing traffic patterns and help track vehicles and moving inventory with the help of tracking devices (Sodero et al., 2019). Given the availability of talent, BDPA implementation allows businesses

to gain possible benefits connected with the development of value and the acquisition of a competitive edge (Gunasekaran et al., 2017). The study of logistics operations is based on the total cost concept, and its goal is to manage and handle the actual flows of raw materials, materials, and finite products, as well as international flows, efficiently and effectively. Under the farm of supply chain management, the competitive advantage is secured by harmonising the logistics function with other company functions and by integrating the logistics chains of all upstream and downstream organisations in order to ensure a high degree of customer service at low prices (Stefan, 2017). It is thus vital for BDPA to consider all parameters when it comes to logistics to enhance and optimize the business overall.

The logistics and transportation industries face a multitude of challenges. As a result, inbound and outbound logistics must adjust to the changing environment. It can no longer be managed using standard planning and control procedures due to its rising complexity (Premm and Kirn, 2015). GPS, bar-coding, RFID, time stamping, and other technologies are allowing businesses to capture more data than ever before complicating decision-making.

Accurate demand forecasting is a challenge for businesses; not knowing what is coming, when it will arrive, and who will need it when can cause resource constraints. Recruiting and training personnel is quite expensive (Sgarbossaa et al., 2020). With shifting fuel prices, the need to optimise routes and staff utilisation is becoming ever more critical. Companies are encountering declining profit margins and capacity restrictions in terms of both physical and human capital, notwithstanding the opportunity to pass part of the fuel costs on to customers via fuel clause adjustment. (Stefan, 2017).

The emergence of Predictive Analytics can help companies to spot previously unnoticed trends and forecast variations, allowing them to better plan for the future. PA also provides a wide range of mathematical enhancements, projects and resource planning and management, simulation system management, decision-making analysis, and many other capabilities, allowing organizations to create detailed models of the business and get a clear picture of current, future, and potential performance (Winkelhaus and Grosse, 2019). Predictive analytics can even aid in developing refuelling plans and maintenance schedules which can be implemented by all vehicle producers and manufacturers, resulting in lower customer fuel costs while also enhancing the performance, efficiency, and longevity of future cars (Hopkins and Hawking, 2018). It also enables better reporting procedures as well as the detection of risk areas such as compliance violations, fraud, and reputational damage. Only a small percentage of businesses make full use of predictive analytics. On the other side, this approach frequently clashes with efforts to keep IT expenditures under control and reduce them. Smart logistics can better aid in improving the transparency and flexibility and be resilient to any consumer demands and market changes. Because "Smart Logistics" will evolve in response to actual technological advancements, it will be time-sensitive, making it necessary to define the current status of the technology (Barreto, Amaral, Pereira, 2017).

2.4.4 Warehousing

For the past five years, multiple sources in warehouses have generated massive volumes of data every second (Ghaouta, El bouchti, Okar, 2018). These are RFID devices, pallet transfer information, weather data, ERP, GPS and IT system data, along with many other business and external data. Companies which invest in BDPA platform and acquire expertise in efficient analytics can improve and enhance their WM operations and become cost effective (Ghaouta, El bouchti, Okar, 2018). Receiving, put away, internal replenishment, order picking, accumulating and sorting, packing, cross docking, and shipping are all examples of warehouse operations. Companies are utilising innovative approaches such as BDPA to gain improved insights which can be used as competitive advantage to reduce the likelihood of various risks, increase efficiency and growth by maximising frequency and transparency in operations, and improve agility to deal with hurdles and challenges (Gupta et al., 2020).
BDPA can provide innovative solutions to deal with WM difficulties such as management of space in warehouses, handling resources, monitoring and overseeing operations, and reduce costs and optimize performances to make better decisions in the WM industry. In addition, data sources in WM can be divided into two categories: internal and external data. Data from ERP systems, pallets, carriages, GPS, weather and traffic data as well as other business, EDI transaction data are all examples of internal data found in company IT systems and databases. External data sources include logistical networks, weather data, mobile apps, such as those from social networking sites, and statistics from data portals (Ghaouta, El bouchti, Okar, 2018).
Although BDPA adoption in WM is still not common, many logistics companies are using it for a variety of purposes like refuelling planning, pricing contracts and negotiations, minimising truck/driver waiting times, enhancing maintenance durations, route planning, deliveries within the business, and detection of drivers prone to cause more accidents (Ghaouta, El bouchti, Okar, 2018).
Warehouse management systems aid in the collection of warehouse operational and process data. The data captured in Warehouse Management systems (WMS) is of three types.
The Master data contains the following-

- Supplier Master
- Item Master
- Customer Master

The Transaction data includes the following-

- Receiving
- Shipping
- Inventory tracking
- Cycle counts

- Inventory adjustments
- Value Added services

Business data results in the understanding of WMS application and configuration based on client requirements. With these three forms of data, Predictive Analytics can extract, analyse and predict a lot more important business information (Andiyappillai, 2019).
Due to the vast number of deliveries, space management is a key component of WM. PA can help in this regard by projecting and anticipating the supply and demand of brands and accordingly, space management can be implemented. Also, costs can be reduced by optimizing redelivery systems (Palakshappa and Patil, 2018). If a company fails to meet the needs of its clients, it risks losing them. Furthermore, a company's reputation can be spoiled as a result of incomplete or non-fulfilment of orders. Getting the right product at the right time to the right consumer is the need for today's logistics environment. Smart businesses can use BDPA to gain a better visibility over the entire range of processes and understand consumer behaviour to provide the best customer service (Awwad, Kulkarni, Bapna, Marathe, 2018). It is vital that warehouses and fulfilment centers extract as many benefits as possible from big data and PA to maximise profits and gain competitor advantage.

2.4.5 Consumers

Consumers are the most important aspect of many industries and most definitely for supply chain organisations. Factors such as globalisation of supply chains, highly competitive marketplaces, volatile product variations and short product life-cycle have made forecasting more challenging (Boone et al., 2019). Big data has led to a new image of Customer Relationship Management (CRM) strategies. Data analysis assists firms in describing client behaviour, understanding their habits, developing appropriate marketing plans, identifying sales transactions, and establishing long-term loyalty relationships (Wassouf et al., 2020). Companies must adopt new activities to capture and improve client happiness and retention as their businesses become more complex and competitive. As seen before, vast amounts of data are captured on a day-to-day basis from every sector of supply chains. Organisations should analyse data to gain insights into customer demographics and psychographics. Customer loyalty can be predicted to identify both consumers who are very loyal to their current provider and customers who are planning to switch to a competitor (Wassouf et al., 2020). Also, impact of social media platforms like Facebook, Twitter, Instagram, Pinterest, etc. has been proving to have a huge impact on buying preferences and perceptions of consumers (Pantano and Gandini, 2017).
Today's most prevalent method of tracking is through social media, credit and debit transactions, IP addresses, loyalty programs and customer emails registered on websites, etc. If the data captured has a variety of information about the consumers, it is considered to be a rich data set with the ability to predict more accurate set of

insights using predictive models (Bradlow, Gangwar, Kopalle, Voleti, 2017). Massive amounts of data acquired in near real-time has the potential to increase understanding of demand and supply forecasting, customer behaviour, and supply chain management. The more a company understands its customers' buying habits and preferences, the more accurate demand forecasts will be received which can help in efficient supply chain decision-making (Boone et al., 2019).

There are many ways that the data is collected for consumer analytics and demand forecasting. There is point-of-sales data where modern point-of-sale systems can record precise information on sales timings as well as goods availability in inventory. This can result in a better view of sales as a pathway to calculate the required stock planning, giving a better sense of demand (Boone, Ganeshan, Jain and Sanders, 2019). Other ways also include the traffic data, in-store data, path data- which suggests how the consumer approaches products, and internet and social media data (Boone, Ganeshan, Jain and Sanders, 2019).

But with such vast amounts of data come challenges. Most organisations still use traditional methods of capturing and forecasting data. More information should ideally lead to better forecasts. But the increasing level of variables and confusing functions lead to difficulties (Feng and Shanthikumar, 2018). Biases from the planners and forecasters also play a major role. Newly accessible data has the potential to decrease the negative consequences of prediction adjustments. Companies are now integrating such systematic approach to have better forecasts (Sagaert et al., 2018). Customer experiences and preferences keep on changing due to impact of external influencing factors like publications, internet, discounts, etc. Connected supply chains which use techniques like targeted promotions and messages, accurate tracking of consumptions, online diagnosis and risk management, can be used by demand planners to capture consumer attention and loyalty. But many organizations fail to inculcate these and thus get improper forecasts. Moreover, privacy and theft issues are increasing on a daily basis and forecasting communities need to take these factors under consideration as well (Boone et al., 2019).

The literature review reflects that even though there are many challenges in PA, the benefits outweigh them in all levels. As predicting the future can reveal many important insights and avoid risks and errors, it is the next step for all organisations to use to their full advantage. Strategies such as just-in-time, improved data prediction and accuracy and lean manufacturing can help in quality management and ongoing market growth (Gupta et al., 2020). It is thus vital for this research to understand the concepts of Big Data Predictive analytics, its types, functions, characteristics and also mainly about Predictive Analytics with this implications and impact on supply chain management and the current challenges faced by organizations in its implementation. It can also be seen that big data analytics and other technologies not only enhance operational effectiveness using analytics methods to gain value and capabilities, but also can give rise to new entrepreneurial options where new businesses can rise with strategic use of these technologies (Sedkaoui, 2018).

3 RESEARCH METHODOLOGY

The main objective of any research study is to find answers and solutions to problems using various scientific methods. It is a long and time-taking process and involves many activities to derive to final conclusion (Bairagi and Munot, 2019). For this research, the researchers use qualitative research methodology. Qualitative methods usually provide descriptive data which is usually concerned with people's feelings and experiences. It is way to approach the empirical world rather than being just a set of data gathering forms (Taylor, Bogdan and DeVault, 2015). Qualitative research is inductive and also works on theoretical frameworks and researchers use the data to reveal useful insights and understandings from the patterns in the data collected (Taylor, Bogdan and DeVault, 2015). Also, this type of research is more complicated and requires guidance and concepts to back up theories. Everyone tends to react differently to different situations and hence it is difficult to derive to predictive conclusions (Bairagi and Munot, 2019). There are few theory-based aspects available to comprehend and then interpret the effect from a managerial view. As a result, qualitative approaches were employed for this research paper so as to better comprehend the variety of perspectives and impressions expressed by the respondents concerning the occurrence (Johnson and Bohle, 2019). Qualitative research focuses on gaining a better understanding of processes, experiences, and the interpretations people place on objects (Aspers and Corte, 2019). But many researches argue with this fact as people's views and opinions are different depending on their personal perceptions and experiences (Taylor, Bogdan and DeVault, 2015).

3.1 Data Collection

The data that is gathered for this research is of primary and secondary types. The primary data for this paper is extracted through the use of questionnaire survey which has been specifically designed to understand and portray the main aim and objectives established. For the purpose of this research, the survey was distributed to a population of around 80 participants. The participants for the research consisted of Supply Chain Analysts and other Supply Chain professionals who have a knowledge about the use of PA in the field. Due to time restrictions and other factors, a total of 63 responses from the respondents have been collected from the surveys.

All participants were provided with the consent form and were intimidated about the survey beforehand. The secondary data has been derived through many research papers and peer-reviewed journals and reports. In addition, the secondary data gathered for the literature study and supporting material has been correctly cited, with

references to the relevant journals, reports, books, websites, publications, and so on. As a result, the study complies with the relevant legal and ethical considerations.

3.2 Data Analysis

The data that has been captured through the JISC survey link was distributed amongst the respondents and has been analysed by the JISC system itself. To identify crucial issues, gather relevant and significant information and analyse the data helps in taking the right course of action (Sekaran and Bougie, 2016). The questions asked were mostly close-ended and easy to interpret. Hence graphical representation of them was easily created. Pie-charts which are effortlessly created, give a very clear and crisp idea about the results. Because of the historically substantial dependence on quantitative methods, qualitative methods such as case studies and grounded theory have become more relevant to practise. Thus, for this research, interpretative approach is also employed to enhance the findings from secondary data.

4 FINDINGS AND DISCUSSIONS

This section illustrates the findings gathered from the primary research survey questionnaire which has been distributed amongst the participants. This section is useful in gaining a better knowledge of the actual impact that PA can have when it is applied in organisations and businesses.

The first question that was asked to the participants was regarding optimized performance by the use of Predictive Analytics in organizations. Majority of the respondents have agreed that PA does help in optimizing the performance of an organization (Figure 1).

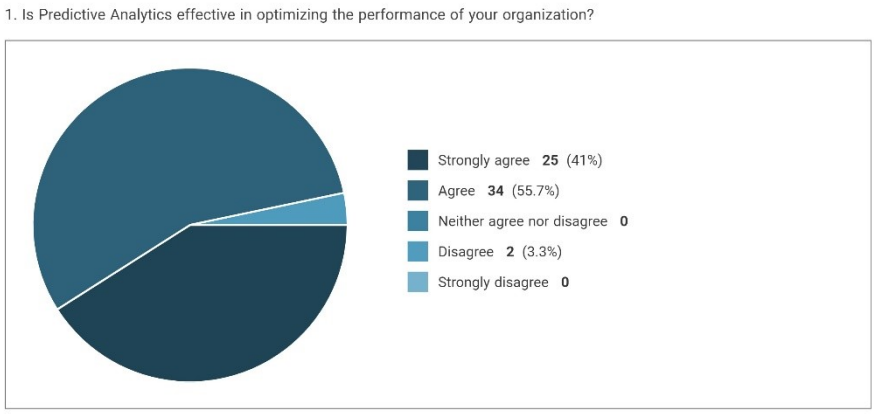

Fig 1. Responses to the first question on PA role in optimization

Predictive analytics is built on people, tools, and algorithms, and operationalising it requires all three (Ogunleye, 2014). Big data enhances organisational performance by complementing information technology with the ability to use it and at the same time aid in better decision making. The enhanced operational performance results into cost-effective solutions that can weather the storm and contribute to overall sustainability. Lean manufacturing, just-in-time strategies and the ability to predict precise data are all part of quality management and can aid in sustainable and long-term growth of the market performance (Gupta et al., 2020). Also due to cost constraints, most large organizations can afford the use of data-driven software. This is where cloud computing is now being used as a cost-effective means to use data to its full potential by smaller organizations and even upcoming entrepreneurial businesses, ultimately enhancing their business models (Naous, et.al., 2017). Business systems can thrive longer with strategic engineering techniques to develop their business models for cloud computing and data analytics (Hosseinian-Far, Ramachandran and Sarwar, 2017).

The next question which was asked of the participants was regarding the use of highly skilled workers in PA. The majority of responders agreed with this statement (Figure 2).

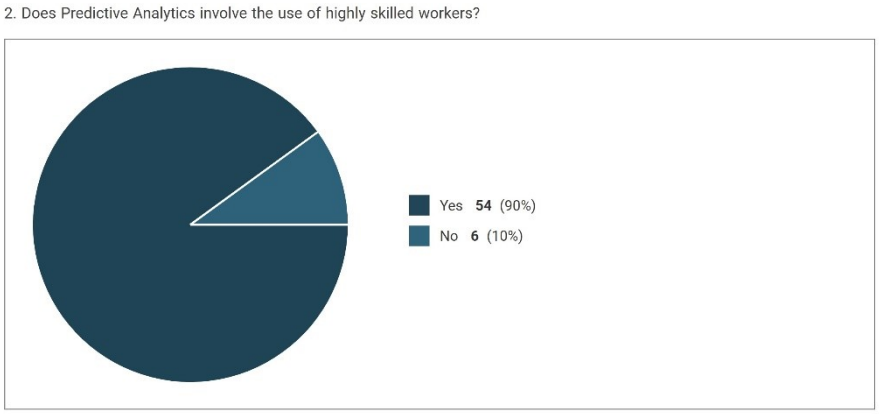

Fig 2. Responses to the second question on the requirement to have highly skilled workers

To attain overall dynamic capabilities, the total organisational performance needs a continuous upgrade of technology as well as people who can use that technology. This leads towards the human component, which not only aids in the establishment of technology, but also plays a critical part in realising its full potential, and at times even outperforms as a competitive advantage for the firm. There are many disadvantages when there is a shortage of skilled labour in organizations like impact on leveraging the value of technological advancements and achieving overall performance. But at the same time, the presence of highly skilled human involvement can have a positive impact not only on developing the knowledge but also making sure that all resources are utilized at full capacity. This is something that cannot be acquired easily (Gupta et al., 2020). It is thus necessary for any organization to acquire a rich and skilled set of resources to have an enhanced environment.

Question three asked of the participants was if PA models provide companies with accurate future insights. Majority responders agreed with the notion.

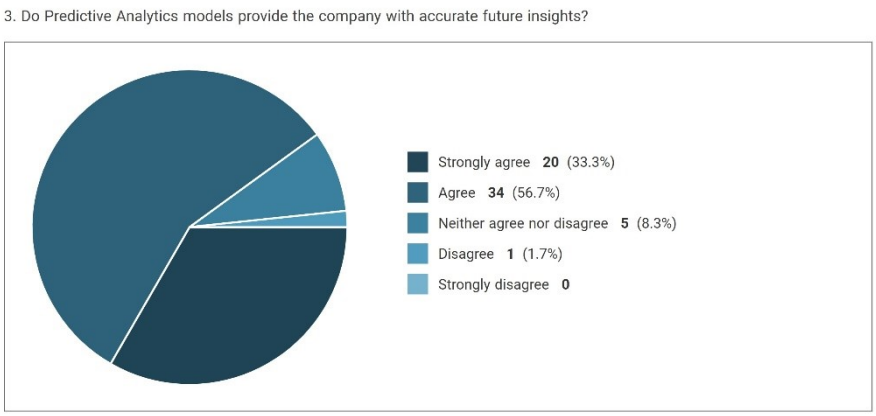

Fig 3. Responses to the third question on the role of PA for insight provision

Predictive analytics predicts future insights by using various simulations, statistics and programming. Most of the supply chains lack the capability to leverage the power of data to gain valuable insights for the organisations. The root causes include a lack of capacity to analyse massive amounts of data and also the ability to use erroneous data, both of which result in immense cost savings (Rowe and Pournader, 2017). This type of erroneous data can even hamper the quality of the predictions generated. Recent technical breakthroughs in data collecting and storage, as well as powerful data analysis tools, particularly for unstructured data, have radically altered the nature of labour and the workplace. Also, it is very important to understand that no algorithm can give 100% accurate results (Tiwari, Wee, Daryanto, 2018). It is thus vital for organisations to improve on their analytics capabilities to gain more accurate and credible insights for optimized performance.

The next query asked to the participants was if Predictive analytics is more effective than other forms of analytics which are- Descriptive, Diagnostic and Prescriptive (Figure 4).

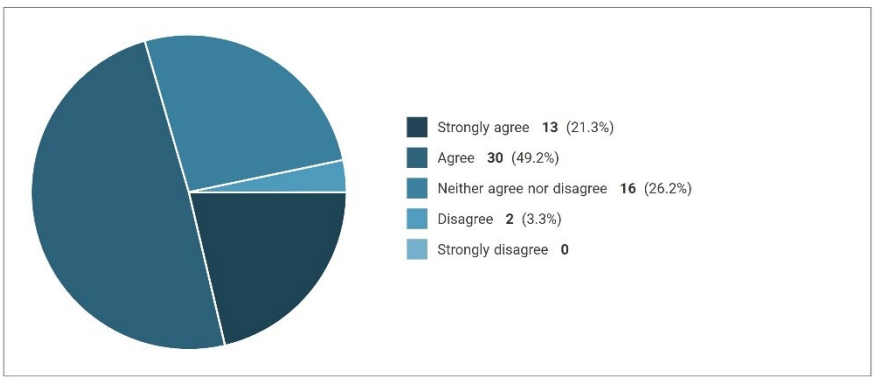

Fig 4. Responses on the comparison between PA and other analytics categories

Descriptive analytics illustrates as to what happened in the past. Diagnostic analytics helps to understand the reason for why it happened in the past and in what way it actually occurred. Predictive analytics helps to anticipate and forecast what can happen in the future. Prescriptive analytics can help in devising solutions after receiving insights. Most of the managers usually prefer the idea of predicting to change than reacting to it (Halim et al., 2018). Therefore, most organizations prefer to use predictive analytics over others. From projecting consumer behaviour and purchase patterns to anticipating sales records, predictive analytics can be applied throughout supply chains. They also aid in forecasting demand for supply chain and inventory planning and also operational management. Predictive analytics can help predict the future or bridge the gap in between the organization's knowledge (Tiwari, Wee, Daryanto, 2018). In the future, predictive data analytics will be the backbone of resilient and adaptable supply chains, allowing businesses to better prepare for changes and uncertainties. They can not only mitigate hazards, but also respond proactively to supply and demand fluctuations (Majumdar, 2021).

The next query that the participants were asked was whether PA model is time-consuming. Here, majority respondents agreed to the notion (Figure 5).

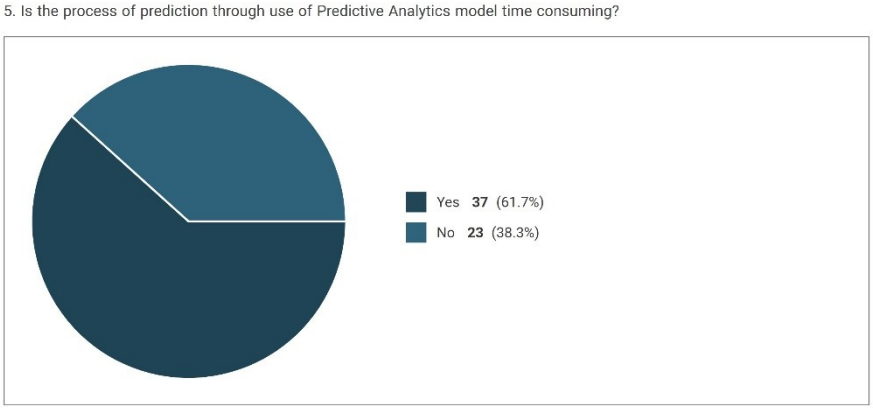

Fig 5. Descriptive statistics on the fifth question

The process of prediction involves many steps. First, it involves defining the project's business goals and intended outcomes, then translating them into predictive analytic goals and tasks. Then the source data is analysed to select the best data and model-building approach and define the scope of the project. The data is then prepared by selecting, extracting and transforming it accordingly. The models are created, tested and validated based on the data prepared to see if they meet the project criteria. The model results are then applied for making business decisions. They are then monitored and maintained to keep the efficiency high at all times. Many experts are of the opinion that the data preparation stage is very tasking and time-

taking. As data comes in all types and forms, it needs to be properly segregated to have accurate prediction models. Moreover, the models that are developed also take time as there are many variables that have to be considered. As a result, most analysts reduce the number of variables in the final model from a few hundred in the initial version to a few dozen. To increase model accuracy, they may need to incorporate new data types or recombine current fields in innovative ways. Model creation is labour-intensive and time-consuming due to this iterative process (Eckerson, 2007).

The next question asked was if PA provides a good return on investment (ROI) to companies. Most of the respondents did agree to this (Figure 6).

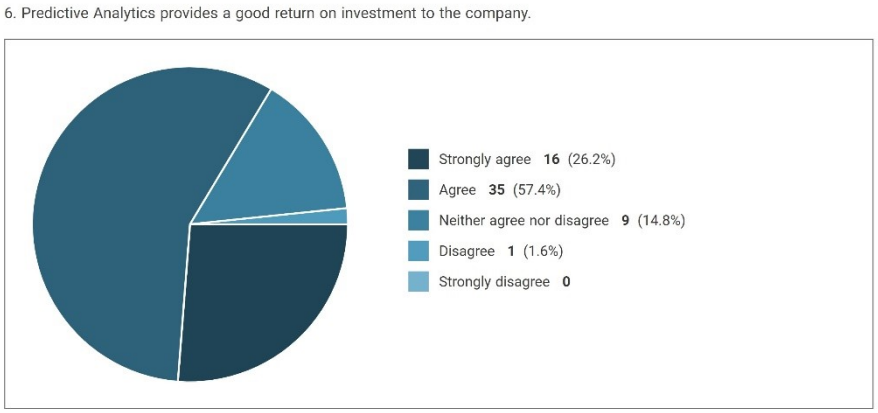

Fig 6. Responses to questions on PA and ROI

Companies can use predictive analytics to improve existing processes, better understand and gauge consumer behaviour and also spot unanticipated opportunities and predict problems before they even take place, providing the companies with a good ROI (Eckerson, 2007). When it comes to PA, people, process and technology have to considered to acquire its full potential. PA has the capacity to provide organizations with a good ROI which depends on the three factors. Although the majority of predictive analytics projects are focused on enhancing individual business processes, having a long-term strategy allows for a more efficient utilisation of predictive analytics and supporting resources. The benefits of predictive analytics projects last for a long time, and companies who use analytics more frequently are more competitive. Predictive analytics projects yield a slew of intangible or difficult-to-quantify benefits, bolstering the case for investing in these tools. Even during difficult economic times, investment in predictive analytics continues to grow at a strong rate (Vesset and Morris, 2011).

With respect to the pricing quotient of PA, most respondents agreed to that fact that it is expensive. But at the same time, good number of respondents chose to opt the option to neither agree nor disagree (Figure 7).

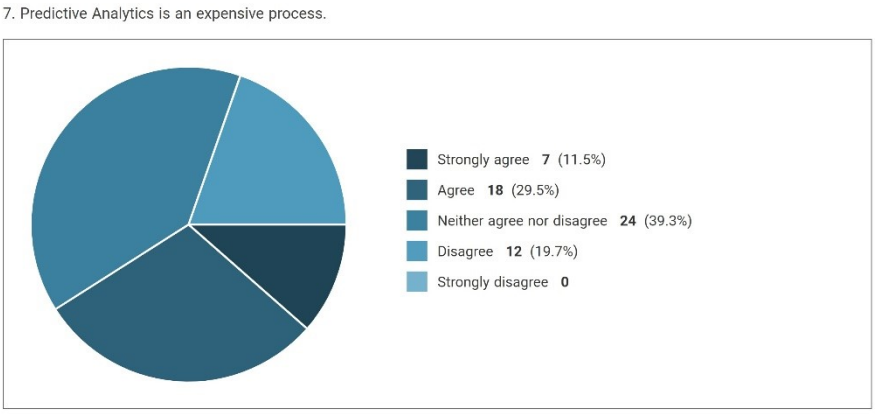

Fig 7. Responses on the value proposition of PA

As PA involves the use of many different aspects and requires skills to understand the technology, the overall investment needed is high. Pricing can depend on a lot many factors like the amount of data available, the extent to which it needs to be cleaned and prepared, the number of skilled employees, technologies used, software needed for visualization, etc. So, the price varies according to what is expected from a project.

In the academic and industry communities, big data trading has become a developing and promising topic. Data is a virtual thing, unlike traditional commodities, with qualities such as variability, variety, volume, velocity, and complexity. Traditional pricing methods and strategies need to be modified and transformed to meet the current environment, so that the true value of big data can be revealed (Liang et al., 2018).

Regarding the reliability of PA, most respondents were of the opinion that it is in fact reliable (Figure 8).

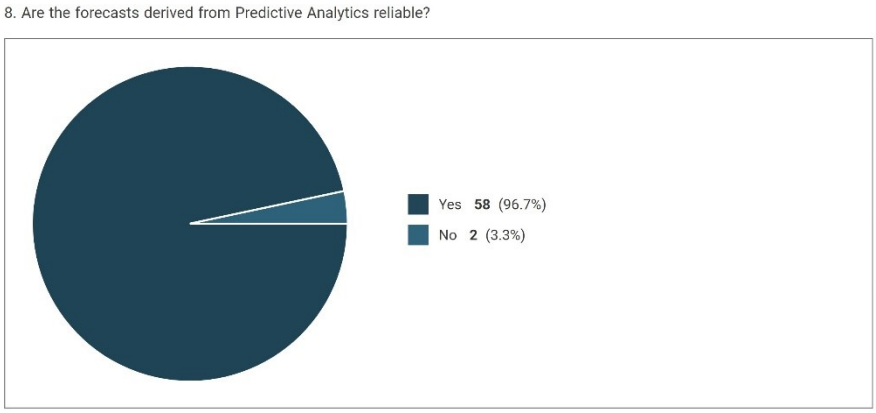

Fig 8. Perceptions on PA reliability

When it comes to PA, there are many factors that determine the accuracy and reliability of the technology. One of the factors that affects the accuracy is the quality of data. If the data quality is bad, it can affect future predictions which in turn will not be reliable. The influence of poor data quality on the validity and interpretations of BD procedures led to the conclusion that data quality and accuracy must be ensured in every proposed strategy (Mazzuto and Ciarapica, 2019). Organisations should therefore invest in data quality control for enhanced results. The use of a BD strategy in the SCM is favourably connected to information interchange and SC connection, implying that BD can assist in overcoming crucial predictive analytics difficulties related to data capture, storage, transfer, and sharing (Gunasekaran et al., 2017) More data will be generated as supply chains become more integrated, resulting in more dependable outcomes.

The next query was regarding whether PA provides companies with a competitive advantage over others. Most respondents agreed to the notion (Figure 9).

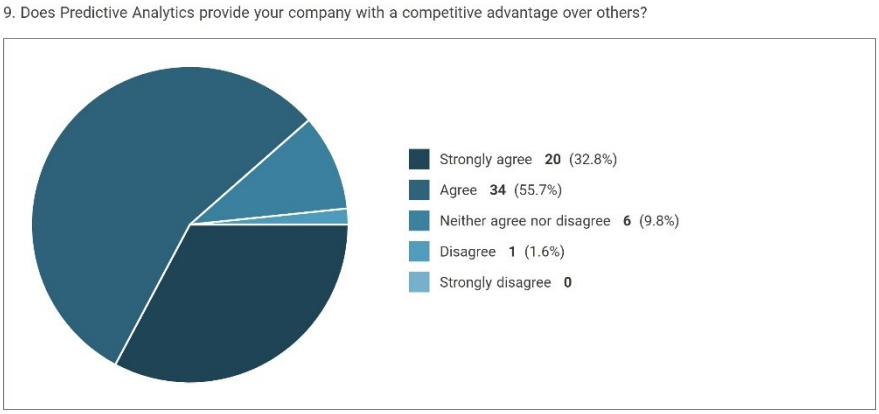

Fig 9. PA and competitive advantage; descriptive statistics of responses

Predictive Analytics has become a popular issue in the analytics world as more companies understand that predictive modelling of accurate customer behaviour and business scenarios is the most effective technique to acquire insights from data analytics. Predictive analytics is also regarded as one of the most important foundations in allowing digital transformation efforts across sectors and business processes all over the world. Additionally, IT companies' increased development and commercialisation of analytics solutions has aided in the expansion of predictive analytics capabilities. As a result, the number of people adopting the technology has increased. When effectively deployed, the technology can allow businesses to achieve business benefits from their data collection (Attaran and Attaran, 2019). As predictive analytics becomes more sophisticated, it will be used to identify the most productive companies in the future. This indicates evolving technological and managerial frontier that increases firm performance while providing a fleeting competitive advantage: organisations that stay on the cutting edge achieve and sustain gains over less data-centric businesses (Brynjolfsson and McElheran, 2019).

The final question asked to the participants was if they would be willing to recommend PA to other businesses or not. Majority responded positively (Figure 10).

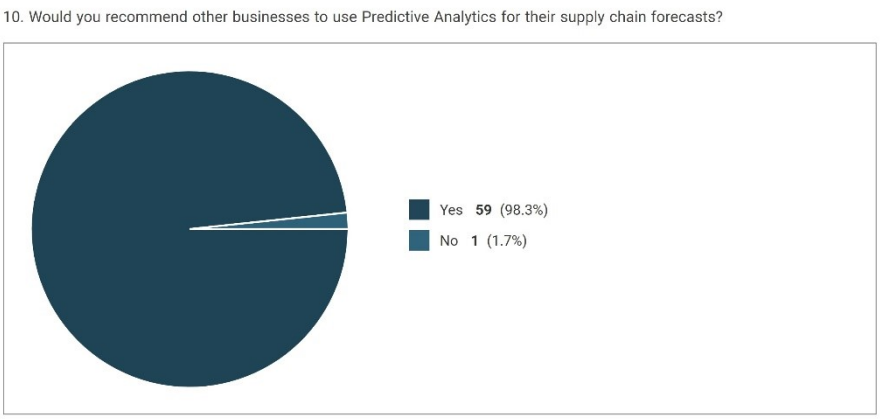

Fig 10. Responses of participants on the suitability of PA for SC forecasts

It is self-evident that, given the benefits that PA and big data can deliver to businesses, the vast majority of them will adopt it. Logistics managers can have a better visibility on many internal processes if technologies like data science and big data predictive analytics can be used at full potential. As companies begin to adopt BDPA, modest benefits gained through initial pilot projects frequently serve as the foundation for expanding implementation to other elements of their operations, allowing managers to rethink their potential capabilities. New goods, services, and even business strategies, along with this shift in perspective, drive enterprises and their SC relations to rethink their entire competitive spot in the whole chain in comparison to competitors (Sodero, Jin, Barratt, 2019). As a result, businesses should push one another to utilise modern technology in order to improve performance and maintain good partnerships. This has the potential to improve both technological and organisational performance.

5 CONCLUSION AND RECOMMENDATIONS

As supply chains are very diversified and complex networks, it is quite essential for organizations and companies to inculcate newer technological developments to better their performance and results. Technologies like ERP systems, Human Capital Management, Predictive Analytics, Business Intelligence, security systems can enhance business models and give better predictions. This can also help predicting employee attrition. All these are very useful tools for entrepreneurship as well (Chornous and Gura, 2020). The goal of predictive analytics is to find deviations and patterns in data and convert into informative business ideas. It can be used to estimate delivery, asset utilisation, maintenance, productivity, and sales prediction, as well as sense and react to risks in supply, demand along with operations. When

estimating demand, predictive analytics allows companies to take into account both endogenous and exogenous elements (Arunachalam, Kumar, Kawalek, 2018). Overall, PA provides a vast array of benefits when used in a systematic manner. Supply chain sectors from procurement, manufacturing, logistics and distribution, warehousing and the end consumers have to understand the technical aspects of big data and predictive analytics to reap the utmost benefits out of it. There have been some concerns and challenges that organisations have faced in appropriately implementing it. The main issues have been with the burdensome data generation, the expertise and skills required and the adoption by industries.

Segregation is a time-consuming and difficult operation that necessitates precision and accuracy. As a result, firms must engage in data management techniques to ensure that data analysis runs smoothly. Big data can help in providing both vertical as well as horizontal vertices of flow of information, which must be supplemented with the technical and management skills required to process it. As a result, it is clear that highly skilled staff can assist in meeting PA needs. Organizations whose primary focus is on long-term business operations may consider adopting a dynamic capability approach so that they can establish not just distinct but also adaptive skills. These dynamic resource capabilities let businesses leverage themselves by allowing them to change their operations and adopt, build, modify and change their internal and external processes. New technologies have the power to reach successful heights with proper planning and development. With immense amount of data, newer business models can be developed to gain profits from multiple sources. Delhivery, Dmall, Flexport are some of the examples of supply chain unicorns which have shown to provide cost-effective platforms for their consumers with the help of data. Young start-ups can make use of the ample amount of information on the internet and grow strategically. With proper guidance, BDPA can deliver competitive advantages in extremely dynamic market settings if nurtured over time.

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