Designing a framework to develop capabilities for adopting AI/ML technologies in the supply chain

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ABSTRACT

In recent decades, supply chain organizations have encountered significant hurdles resulting from unexpected environmental and operational changes. Supply chain organizations struggle to keep up with rapidly changing customer demand, excellent operations planning, and the constantly changing state of business processes in an increasingly VUCA (volatility, uncertainty, complexity, and ambiguity) environment. As a result, innovative analytical technologies can be implemented in supply chain operations to overcome the hurdles and manage the operations. For the successful implementation of innovative analytical technologies like AI/ML in supply chain operations, organizations need to develop essential capabilities. In order to focus on essential capabilities, the objective of this thesis is to design a framework to develop data management, analytical, and performance management capabilities for implementing AI/ML technologies in supply chain operations.

To achieve this objective, we started by conducting a systematic literature review related to the fields of supply chain operations, applications of AI/ML in the supply chain, metrics to assess the applications of AI/ML in the supply chain, and required capabilities for adopting the AI/ML technologies. From the literature review, we found that the AI/ML technologies have been extensively applied to overcome challenges in all supply chain fields, for instance, in operations planning, production planning, supply planning, inventory replenishment, and logistics planning. Additionally, from the literature, we found essential capabilities required for adopting AI/ML technologies and improving the overall performance of the supply chain operations.

Based on this literature review, we constructed a framework. The framework consists of three primary capability elements, each of which has two sub-elements. The first element of the framework is data management capability, and its sub-elements are data governance and data quality. The primary goal of data management capability is to improve supply chain maturity by maintaining data accuracy and increasing visibility and control throughout the supply chain in order to maximize agility and responsiveness. The second element is analytical capability, and its sub-elements are business case development and AI/ML technologies implementation. Analytical capability plays an essential role in proposing suitable AI/ML technologies in the supply chain fields like planning, sourcing, production, and delivering. It also helps to automate, augment and enhance customer experience and decision-making process. The third element is performance management capability, and its sub-elements are the six sigma DMAIC method and KPIs dashboard development. The performance management capability helps to analyze, monitor, and improve their existing supply chain management processes to beat market competition and stay competitive.

In the final stage, the framework is evaluated by performing interviews with three domain experts. The evaluation outcome aimed to determine the usefulness, feasibility, and impact of the supply chain

capability framework when adopted in the organization. The results from the evaluation determine that the overall strategy and elements of the framework will be useful and found to be essential pillars in addressing the critical issues that companies face. Adoption of the framework would be feasible but depending on the organization's structure and goals. Whereas implementing the framework in organizations can have considerable benefits of improving productivity and customer satisfaction.

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1. INTRODUCTION

Supply chain operations are an integrated set of business functions encompassing raw material acquisition to final customer delivery. The Operations and Supply Chain Management (OSCM) includes a broad area covering both manufacturing and service industries, involving sourcing, materials management, operations planning, distribution, logistics, retail, demand forecasting, order fulfillment, and more. The effective supply chain can help satisfy customer service requirements, determine inventory placement and levels, improve organizational performance and profits, and create effective policies and procedures to coordinate supply chain activities and decision-making strategies (Ware, 1998). Plan, Source, Make, Deliver, Return and Enable are the six primary supply chain operations processes. According to (Vegter et al., 2020), the key processes are subdivided into some pre-defined sub-processes that serve as the building blocks for defining every supply chain operation.

- The process Plan represents the planning and control activities.
- The process Source means identifying and selecting sources of supply, scheduling deliveries and receipt of products, and transferring the product.
- The Make process involves converting materials into products or services.
- The Delivery process reflects the execution of orders: collection, packaging, delivery, and invoicing.
- The reverse flow of the goods from the end-user is the process Return.
- The process Enables the activities related to supply chain management to be defined.

Sales and operations planning (S&OP) is an integrated business planning process and the best practice in the supply chain; its key objective is to balance customer demand with supply capabilities (Nemati et al., 2017).

Business organizations have faced enormous challenges in recent decades due to unprecedented outbreaks of disease. The scope of these organizations' challenges depends mainly on the severity of the attacks concerned. A widespread public health incident, such as an epidemic or pandemic, can have significant negative consequences for companies and supply chains, such as lowering productivity and profitability and propagating disruptions through supply chains (known as ripple effects), compromising their stability and long-term sustainability (Chowdhury et al., 2021). The activities in the supply chain are interconnected; therefore, a disturbance in one function has a ripple effect that affects demand planning, supply planning, manufacturing, transportation, logistics, and relationships, potentially causing the supply chain to collapse completely (Yuen et al., 2020).

The adoption of digital technologies in manufacturing becomes increasingly important in the current global business environment to address these issues. In the last decade, manufacturing firms have been exploring how to use emerging digital technologies, e.g., the Internet of Things (IoT), Big Data Analytics (BDA), and Artificial Intelligence (AI), in their production and Supply Chain Management (SCM) (Yang et al., 2021). These technologies are seen as promising means to improve supply chain functions, such as procurement, logistics, scheduling, and planning.

Building a more agile and resilient supply chain with linkages, processes, and activities under complex environments requires monitoring, forecasting, prediction, and optimization. Artificial Intelligence (AI) applications have emerged in several different sub-fields of the supply chain (Riahi et al., 2021). AI allows systems without human intervention to make resourceful decisions and execute tasks automatically. Companies take advantage of AI and machine learning in different areas such as warehousing, logistics, and supply chain management.

Many definitions of AI exist, depending on what AI wants to accomplish. They are usually divided into two groups based on a conscious human being and rational behavior. (i) systems that think and act like human beings, and (ii) systems that think rationally. AI can be described from a general viewpoint as a machine able to reproduce human intelligence, with the ideal trait for rationalizing and taking actions that are most inclined to achieve a specific goal (Čerka et al., 2015).

AI enables the implementation of predictive methods that allow for the rapid detection and more efficient minimization of threats or disruptive incidents in the supply chain. It allows users to recognize trends in the supply chain. AI can easily define appropriate supply chain data and use algorithms, allowing managers to create models that help them better understand how each process operates and identify areas for improvement (Ni et al., 2020).

Businesses are looking ahead to optimize their supply chain and develop their capabilities as globalization continues, bringing many changes to the market, demand, data availability, management, and more. These changes require concerned business organizations to maintain competitiveness by avoiding demand uncertainty, disruptions, and financial risk. As a result, many capabilities needed to be developed within the supply chain in order to achieve the highest rankings in global competition (Giannakis & Papadopoulos, 2016). In response to these business environments, there is a growing recognition of the value of advanced analytical tools and applications in supply chain operations by developing dynamic supply chain analytical capabilities (B. K. Chae & Olson, 2013).

1.1 PROBLEM STATEMENT

Many traditional IT systems are dedicated to supporting various business processes in supply chain operations, such as ERP (Enterprise Resource Planning), MES (Manufacturing Execution System), PPC (Production Planning & Control), SCADA (Supervisory Control and Data Acquisition) (Hao, 2021). Most of the supply chain operations have been digitalized with advanced IT technologies. Due to the complex nature of the supply chain, rapidly changing consumer demand, unstructured decision problems, and the continuously changing state of business processes, specific solutions are not intelligent enough (i.e., not able to act rationally depending on the environment) and are not very appropriate for the modern supply chain management (Schiavone, 2017). It is critical to operating with the highest efficiency in all significant activities and business flows in the supply chain to develop intelligent, rapid, and efficient business response systems. As a result, more advanced IT systems are needed to deal with multi-level, highly variable industrial operations problems in the digitalization process (Seyedghorban et al., 2020).

Since AI in the supply chain is gaining more attention over the years, the themes related to the field are still relatively new or under development. In recent years these fields have known an increase in terms of research. In addition, with the increasing VUCA (volatility, uncertainty, complexity, and ambiguity) aspect of the environment in which the supply chain operates today, especially during a crisis like a coronavirus pandemic in 2020, the supply chain needs to establish technologies such as AI/ML that enable prediction, forecasting, decision-making assistance, and aid in the various supply chain processes (Riahi et al., 2021). The implementation of AI technologies can present significant challenges for organizations with increased scope and depth of potential applications and greater integration of AI. Challenges include social, economic, data, organizational, and management challenges and technology implementation challenges (Dwivedi et al., 2021).

Companies nowadays invest heavily in information technology to monitor products and operations, automate transactions, and optimize inventory levels and other supply chain decisions, such as enterprise resource planning, radio frequency identification, and more. Large amounts of data are generated by these technologies, which flow in real-time into every sector of the global economy. With approximately 2.5 exabytes of data produced every day and that volume doubling every three years, the size of data production is significant (Yu et al., 2018). Lack of appropriate data applications and data management can have substantial tangible and intangible losses for businesses. The costs of inappropriate data processing have been estimated to be as high as 8% to 12% of an average organization's revenues and can account for up to 40% to 60% of a service organization's expenses; this leads to annual losses estimated to be in the billions of dollars (Hazen et al., 2014).

Adopting AI/ML technologies in supply chain operations, organizations need to develop the capability to manage data, support supply chain processes with analytical tools, and monitor supply chain performance (B. K. Chae & Olson, 2013). Capabilities are defined as complex bundles of skills and accumulated knowledge that enable firms to coordinate activities and use their assets (Yu et al., 2018).

Hence, this research aims to design a framework for developing data management, analytical, and performance management capabilities for efficiently managing and improving the data quality, adopting the analytical technologies, and monitoring the performance of the overall supply chain operations.

1.2 Research Objective

The primary objective of this research is to design a framework to develop capabilities for implementing AI/ML technologies in supply chain operations. This approach is believed to enhance the data quality for accurate forecasting using appropriate predictive AI/ML technology implementation and monitoring the overall supply chain operations to track the effects of AI/ML technologies and support the decision-making process.

The following steps are taken to achieve the stated objectives:

- Conduct a literature review regarding applications of AI/ML technologies in supply chain operations
- Decide on what information will be used for this research to design the artifact
- Describe the proposed framework
- Evaluate the proposed framework
- Discuss the limitation, further research, recommendations, and the results

1.3 RESEARCH QUESTIONS

The research question that is raised and answered in this study is:

How to develop the capabilities for effective applications of AI/ML technologies in supply chain operations?

In order to answer this question, the following sub-questions were derived from the

main question:

- RQ1 - What is found in the literature about the applications of AI/ML technologies in the fields of supply chain operations?

- RQ2 - According to the literature, which problems in the supply chain operations have been addressed using AI/ML technologies?

- RQ3 - What metrics are reported to be helpful to assess the application of AI/ML in supply chain operations according to published literature?

- RQ4 – According to the published literature, which capabilities are essential for implementing AI/ML technologies in supply chain operations?

- RQ5 – How to design the framework that helps develop the capabilities for applying AI/ML technologies in supply chain operations?

- RQ6 – Is the framework finds useful and relevant by the practitioners?

1.4 RESEARCH METHODOLOGY

In order to ensure a stable research framework and methodology, the Design Science Research Methodology (DSRM) by (Peffers et al., 2007) is used. This research framework is commonly used for Information system research in Design Science. In other words, the DSRM model is used in the designing of software (artifact/prototype) that is reused in the context of a research field and evaluating that software (artifact/prototype) in the intended context.

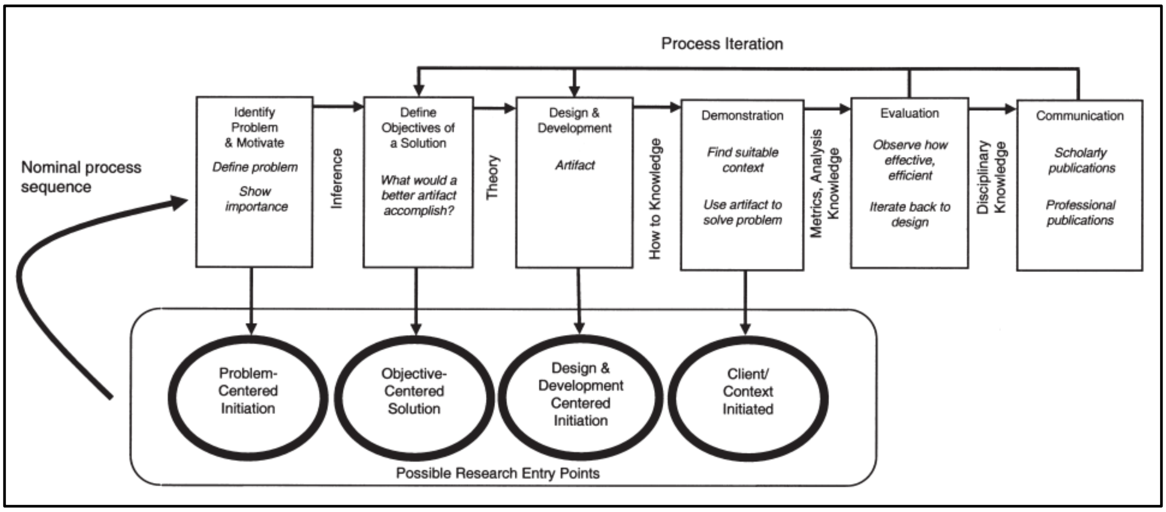

Figure 1 DSMR Process Model (Peffers et al., 2017)

The same steps from the DSRM are followed for conducting this research, as shown in Figure 1.

- The first step includes the "Identification of the problem and motivation." In this step, the problem will be identified, and a solution will be proposed. The motivation of the research and the research questions are presented. This is mainly covered in Chapter 1 of this thesis.
- The second step is "Defining the objectives of a solution." In this step, the objectives of this research are presented, and a road map is created accordingly, considering the literature in reference disciplines. This will result in a template for the structure of the research output. This step uses inferences to determine what would a better artifact accomplish by solving the earlier stated problem. This is mainly covered in Chapters 1 and 2.
- The third step is the "Design and development" of the artifact. In this step, the activity includes determining desired functionality and the architecture for each solution element. The process consists of defining the required input and the necessary actions for reaching the desired output. It is explained in chapter 3.

- The fourth and fifth step is the "Demonstration and Evaluation" of the artifact. In this thesis, the artifact from step 3 is evaluated by conducting semi-structured interviews to observe its usefulness and impact. This step is explained in Chapter 4 of the thesis.
- The final step is "Communication," which will be done in the master thesis defense after submitting the thesis report.

1.5 Research Structure

This study is structured following the DSM framework. Chapter 1 present the introduction of the topic, research questions, objectives, and the methodology which will define the whole course of the study, then Chapter 2, which is the literature review, where the problems and applications of AI/ML technologies are presented along with the performance metrics and capabilities in the supply chain. Chapter 3 presents the design and development of the framework, which is evaluated by conducting interviews with experts in chapter 4. Finally, the paper concludes with a discussion about the contribution of this study and recommendations for further research in chapter 5.

2. LITERATURE REVIEW

2.1 RESEARCH METHODOLOGY

As a research methodology for this study, the systematic literature review (SLR) method proposed by Kitchenham and Charters (Group, 2007) has been chosen. Following their guidelines, our SLR was conducted in three stages: planning, conducting, and documentation. The first stage of planning includes formulating research questions and developing a review protocol. The second stage is about performing research: deciding on exclusion and inclusion criteria, relevant databases, and performing the search. The third stage, documentation, is a study selection part, where the list of included and excluded studies is developed, and the quality of primary studies is assessed (Figure 2).

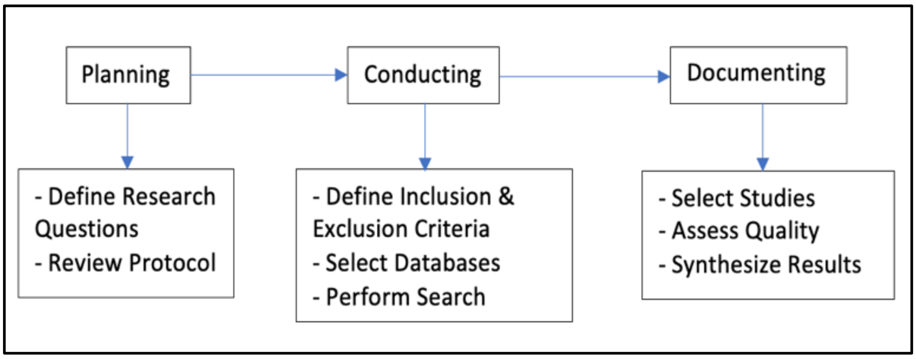

Figure 2 SLR Method Process

2.2 LITERATURE REVIEW RESEARCH QUESTIONS

The research questions are built to achieve knowledge about the application of AI/ML in supply chain operations, current problems, performance metrics, and capabilities required for managing the supply chain.

RQ1. What is found in the literature about the applications of AI/ML technologies in the fields of supply chain operations?

RQ2. According to the literature, which problems in the supply chain operations have been addressed using AI/ML technologies?

RQ3. What metrics are used to assess the application of AI/ML in supply chain operations?

RQ4. According to the published literature, which capabilities are essential for implementing AI/ML technologies in supply chain operations?

The motivation behind RQ1 is to examine in detail the application of AI and ML technology in supply chain operations and Sales and Operations Planning (S&OP). RQ2 is motivated by exploring the existing issues in supply chain operations and S&OP addressed with AI/ML applications. According to published literature, the motivation for RQ3 is based on the expectation that the specific results of the introduction of AI/ML are measurable across the supply chain operations and S&OP. These measures will become indicators of the effectiveness of AI/ML in organizational operations. The motivation for RQ4 is to find and understand the critical capabilities required for adopting innovative technologies in supply chain operations.

2.3 Search Process

In the process of searching for articles and academic works related to the research topic, the following scientific publication databases were accessed:

- Scopus
- Taylor and Francis
- ScienceDirect – Elsevier
- MPDI
- Emerald

These libraries have been carefully selected to include a wide range of highly relevant publications, conference papers, and journals, emphasizing the uses of AI, ML in supply chain operations, supply chain problems addressed by AI, ML technology, and performance measurement metrics and capabilities.

- For RQ1, the search keywords used are "AI/ML", "Applications of AI/ML", "Supply chain operations", "S&OP.
- For RQ2, the phrase used for search is "problems in supply chain and S&OP, "AI/ML impact on supply chain and S&OP challenges. "Challenges and application of AI/ML in supply chain and S&OP".
- For RQ3, the search keywords used are "supply chain performance metrics", "AI metrics", "ML metrics."
- For RQ4, the search keywords used are "supply chain capabilities" "AI capabilities."

2.4 Inclusion and Exclusion criteria

In searching for scientific papers, the formulated inclusion and exclusion criteria suggested by Kitchenham and Charters (Group, 2007) were used. These Inclusion criteria are the following:

- The articles provide an answer to at least one RQ.
- The articles are about applying AI/ML in supply chain operation.
- The article is peer-reviewed.
- The article is in English.

In order to narrow results, furthermore, we formulated the following Exclusion criteria:

- The article is not downloadable from the university's libraries.
- The article mentions AI/ML only as a side theme and does not term AI/ML as the central subject of the paper.
- The article is an old version of a more recent paper.

In order to apply the inclusion and exclusion criteria, it is necessary to read the following sections of each paper:

- Title and Abstract
- Introduction

Besides, an extensive search is also performed by checking the author's name and related works.

2.4.1 Study Selection

In the process of searching and selecting scholarly articles, 380 articles were examined from the mentioned databases. The articles are sorted and evaluated based on the inclusion and exclusion criteria. Besides, these articles should be answers to research questions. The papers are categorized into three categories: Yes / No / Maybe. Articles labeled "Yes" are synthetic articles, and they must focus solely on the research topic. These articles refer to AI / ML, supply chain capabilities, supply chain operations, and S&OP as the subject of study. The articles labeled "Maybe" are only partially related to research questions. Articles labeled "No" do not answer research questions. Therefore, they were removed from the rating panel. Total 54 articles are considered for the study.

2.4.2 Quality Assessment

As directed by Kitchenham and Charters (Group, 2007), evaluating the quality of articles should be based on the following questions:

QA1: Do these articles have properly defined research objectives and/or research questions? Are the research questions and objectives clear?

QA2: Are the research results of these articles determined based on actual evidence?

QA3: What research methods do these articles use? Was the research method used in those papers systematic?

The goal of QA1 is to determine the correctness of academic papers and whether or not those articles directly define the research purpose and question. QA2 aims to evaluate the credibility of such articles. QA3 seeks to check the quality of the article through the research structure. So these review questions contribute to improving this study's quality.

2.4.3 Executing the steps

Table 1 shows the number of papers found per source based on the search commands (Section 2.3, Search process) in selected databases. The initial search was performed in five databases resulting in 380 papers in total, of which 90 were selected based on the criteria outlined in the previous sections. After examining, there were 35 duplicate works. So, this study reviewed 54 articles to find reliable information.

Sources	RQ1	RQ2	RQ3	RQ4	Total
Scopus	9	1	2	2	14
Taylor and Francis	4	3	1	1	9
ScienceDirect – Elsevier	10	6	1	5	22
Emerald	3	-	4	1	8
MPDI	-	1	-	-	1
Total selected papers	**26**	**11**	**8**	**9**	**54**

Table 1 Articles Found and Selected Per RQs

2.5 Results

The following sections present the selected papers and the findings aiming to answer each of the research questions.

2.5.1 What is found in the literature about the applications of AI, ML technologies in fields of supply chain operations?

In order to answer RQ1, the data have been categorized into five key fields of the supply chain. The five key fields are organized into subfields to illustrate the application of AI/ML technologies in each field, presented in Table 2.

Field	Sub-fields	Sources
Sales planning	Sales forecasting	(Chang et al., 2008), (W. I. Lee et al., 2012)
	Sales promotion	(O'Donnell et al., 2009)
	Pricing	(Shakya et al., 2010)
	Marketing decision support	(Stalidis et al., 2015)
	New products specification design	(Kwong et al., 2016)
	Product life-cycle management	(Taratukhin & Yadgarova, 2018)
Logistics	Inbound logistics processes	(Knoll et al., 2016)
	Logistics systems automation	(Klumpp, 2018)
	Logistics workflow	(Ho et al., 2006), (C. K. M. Lee et al., 2011)
Production	Production mentoring	(Guo et al., 2015)
	Production forecasting	(Elsheikh et al., 2021), (NEGASH & YAW, 2020)
	Production planning and scheduling	(Ławrynowicz, 2008)
	Quality control and improvement monitoring	(Taylan & Darrab, 2012)
	Product line optimization	(Waschneck et al., 2018)
Supply Chain	Demand forecasting	(Amirkolaii et al., 2017), (Mobarakeh et al., 2017), (Efendigil et al., 2009)
	Supplier selection	(Ferreira & Borenstein, 2012), (Vahdani et al., 2012)
	Supply chain network design	(Zhang et al., 2017)
	Supply chain risk management	(Baryannis et al., 2019)
	Inventory replenishment	(Sinha et al., 2012)
S&OP	Integrated Business Planning	(Schlegel et al., 2020)

Table 2 Results for RQ 1

The review indicated that the applications of AI/ML in supply chain operations enable supply with intelligence that they can use to trigger a transformational increase in operational and supply chain efficiencies and a decrease in costs where repetitive manual tasks can be automated. The applications of AI, ML have been leveraged in supply planning, production, logistics, and operational planning.

- *Sale planning*

In total, seven articles have been assigned to the field of sales planning. Three articles independently refer to sales: two for sales forecasting and one for promotion. (Chang et al., 2008) and (W. I. Lee et al., 2012) both have proposed hybrid AI models for improving the sales forecast accuracy in different industries. (Chang et al., 2008) have developed the fuzzy case-based reasoning (FCBR) model by incorporated the fuzzy theory into the well-known CBR AI technique to improve sales forecast accuracy. (W. I. Lee et al., 2012) proposed an AI hybrid sales forecasting model called ECFM (Enhanced Cluster and Forecast Model) by integrating SOM and RBF neural networks to boost revenue forecast accuracy, which will significantly help enhance the company plan's efficiency and increase revenues. (O'Donnell et al., 2009) using the online system, they have shown that the genetic algorithm GA effect can help reduce the impact of the bullwhip effect and cost and helps supply managers predict the reorder quantities along the supply chain and plan for the promotions. (Shakya et al., 2010) have proposed the pricing system model using five different AI techniques. Regardless of the demand model used, this method will create pricing policies for a wide range of products and services. (Stalidis et al., 2015) suggest a framework for marketing decision support that includes ANN technology. (Kwong et al. 2016) proposed the methodology for integrating effective design, engineering, and marketing to define new products' design specifications using GA and fuzzy models. The proposed method mainly involves the development of customer satisfaction and cost models. (Taratukhin & Yadgarova, 2018) suggested a multi-agent system (MAS) approach for product life-cycle management (PLM).

- *Logistics*

Four articles belong to the logistics field. One refers to inbound logistics; (Knoll et al., 2016) have presented an approach to predictive inbound logistics planning using machine learning (ML) technology. (Klumpp, 2018) proposed a multi-dimensional conceptual framework to distinguish between better- and worse-performing human–artificial collaboration systems in logistics with an objective of efficiency and sustainability improvement in logistics operations. (Ho et al., 2006) have developed the hybrid logistics workflow optimizer (LOW) with the combination of On-Line Analytical Processing and Genetic Algorithm to increase efficiency and productivity of logistics process to enable the decision-makers to cope with a continuously changing and unpredictable environment. Whereas (C. K. M. Lee et al., 2011) have examined the combination of advanced technologies like AI and RFID that can enhance the logistics workflow system for capturing updated information and deploying relevant knowledge, thus facilitating effective demand management.

- *Production*

Total six articles pertain to the production field. Two articles refer to production forecasting, and both focus on production forecasting using ANN technology. (NEGASH & YAW, 2020) propose an ANN model to predict a water flooding reservoir's oil, gas, and water production rates. Whereas (Elsheikh et al., 2021) suggest a long short-term memory (LSTM) neural network model is employed to forecast the yield of the investigated solar stills. (Guo et al., 2015) have proposed an intelligent decision support system architecture based on radio frequency identification (RFID) to handle production monitoring and scheduling in a distributed manufacturing environment. The proposed RFID architecture has a high degree of extensibility and scalability, making it easy to combine with manufacturing decision-making and production and logistics processes in the supply chain. (Ławrynowicz, 2008) suggested a methodology for supporting production planning and scheduling in the supply chain by combining AI with an expert system and a genetic algorithm. The proposed solution addresses the issues in the following order: it fixes the production problem first and improves the scheduling issues. (Taylan & Darrab, 2012) demonstrate using the AI techniques to suggest a fuzzy control charts design approach to monitoring quality. (Waschneck et al., 2018) propose a deep reinforcement learning technique for optimization scheduling and achieving the industry 4.0 vision for production management by incorporating Deep Q Network with user-defined objectives.

- *Supply chain*

Eight articles have been reviewed in the supply chain field. Three articles in the supply chain field are concerned with demand forecasting. (Amirkolaii et al., 2017) and (Mobarakeh et al., 2017) have presented a survey on the best forecasting method suitable for highly uncertain and unpredictable demands and subsequent inaccurate forecasts, which has severe financial consequences in the same industry. (Amirkolaii et al. 2017) suggested an ANN technique is more effective, whereas (Mobarakeh et al. 2017) suggested Boot Strapping (BS) method. (Efendigil et al. 2009) have presented the methodology for forecasting using ANN and fuzzy techniques to manage the fuzzy demand with incomplete information and manage the uncertain customer's demand. Two articles focus on supplier selection. (Ferreira & Borenstein, 2012) have suggested a fuzzy Bayesian supplier selection model for ranking and evaluating suppliers.

In contrast, (Vahdani et al.,2012) introduced the linear neuro-fuzzy model to predict the performance rating of the supplier. (Zhang et al.,2017) have proposed a bio-inspired algorithm to design optimal supply chain networks in a competitive oligopoly market. (Baryannis et al., 2019) have focused on a supply chain risk prediction framework using data-driven AI techniques for supply chain stakeholders, helping them make decisions to mitigate or prevent risks from occurring. (Sinha et al., 2012) developed a co-evolutionary immuno-particle swarm optimization with a hyper-mutation (COIPSO-PHM) algorithm to solve inventory replenishment in the relationship between distributed plant, warehouse, and retailer.

- *S&OP*

(Schlegel et al., 2020) have suggested that big data analytics' implementation benefits enable advanced integrated business planning and S&OP dimensions, such as meetings and collaboration, organization, performance measurement, and IT, to evolve according to the prevailing maturity stage.

2.5.2 According to the literature, which problems in the supply chain operations have been addressed using AI/ML technologies?

In order to answer the RQ2, the results in Table 3 are classified and presented according to the SCOR model's five main fields: plan, make, source, delivery, and enable. The findings were classified into current supply chain operations challenges that AI/ML technologies can help to address.

SCOR	Challenges	AI/ML Technologies	Sources
Plan	High volatility, uncertainty, irregular, and fluctuating demand of the products and market.	Artificial Neural Network (ANN)	(Gallego-García & García-García, 2021), (Amirkolaii et al., 2017)
		Support Vector Machine (SVM)	(Gecevska, 2017, p. 403)
		Hybrid AI (ARIMAX)	(Feizabadi, 2020)
	Planning under lead time uncertainties	Genetic Algorithm (GA)	(Hnaien et al., 2009)
Source	Delay in the supplier selection process, and constraints in supplier relationship management.	ANN	(Choy et al., 2004)
		Hybrid AI	(Lau et al., 2005)
Make	Complexity in monitoring	ANN, Agent-based system	(Monostori, 2003)
Deliver	Service management under uncertain environment	Deep learning	(Ren et al., 2020a)
Enable	Complexities in measuring and evaluating organization performance	Fuzzy logic	(Arshinder et al., 2007)

Table 3 Results for RQ2

Changes in consumer demand and behavior are driving transformations in the global supply chain operations. Satisfying customer expectations with complexities in the operations is challenging. The results (Table number) indicate that the new innovative AI, ML solutions are helping supply chain industries manage risk, handle challenges, remain competitive, and future-proof their investments.

Five articles have addressed the wide range of supply and demand planning issues tackled by techniques of AI. (Gallego-García & García-García, 2021) have developed the methodology to propose the predictive model using the ANN technique to implement S&OP with higher accuracy and stability under high volatile market demand planning issues. Whereas (Amirkolaii et al., 2017) suggest that ANN could be the best AI technique to balance the demand, supply, and inventory for fulfilling customer satisfaction in irregular and uncertain demand fluctuation scenarios. (Gecevska, 2017, p. 403) has developed the support vector machine (SVM) to forecast accurate demand to avoid the uncertainty effects on the supply chain operations and planning due to the fluctuating demand of the products. Whereas (Feizabadi 2020) has developed a hybrid AI demand forecasting method based on machine learning (ML) and neural networks to overcome financial and coordination constraints in the supply chain operations and management caused due to rapidly evolving consumer demand. (Hnaien et al. 2009) suggest genetic algorithm as the most suitable technique in supply planning under lead time uncertainties for two-level assembly systems.

Two articles belong to the source field. (Choy et al. 2004) and (Lau et al., 2005) have focused on customer selection, customer relationship management, and purchasing information.

(Choy et al., 2004) have designed an intelligent supplier relationship management system using the ANN technique to avoid the delay in the supplier selection during new product development with high accuracy. Due to the volatile marketplace and delay in selecting the supplier partners (Lau et al. 2005) proposed a hybrid AI knowledge-based system that encompassed online analytical processing (OLAP) applications and neural networks for maintaining procurement information and choosing supply partners on time. (Monostori, 2003) have highlighted monitoring and managing various changes and uncertainties in manufacturing process issues in a complex manufacturing environment and proposed ANN and Agent-Based systems more suitable in complex manufacturing environments.

(Ren et al., 2020b) have proposed deep learning-based one-step integration optimal decision-making approach to tackle logistics service demand management challenges under a highly uncertain environment. (Arshinder et al., 2007) have proposed a fuzzy logic approach combined with the analytic hierarchy process (AHP) to address the challenge in measuring and evaluating the coordination between the supply chain partners in the organization regarding coordination, contract agreement, communication, and information sharing, and use of information technologies.

2.5.3 What metrics are used to assess the application of AI/ML in supply chain operations?

The results for RQ3 in Table 4 are categorized into fields and metrics techniques to provide an overview of the types of metrics and techniques used to measure the supply chain performance, S&OP, and AI/ML.

Fields	Metrics techniques	Sources
Supply chain performance	AHP, PGP, ANP, DEA	(Bhagwat & Sharma, 2009), (Trivedi & Rajesh, 2013), (Balfaqih et al., 2016), (Drzymalski et al., 2010), (Wong & Wong, 2007)
S&OP	Performance measurement framework	(Hulthén et al., 2016)
AI/ML	RMSE, MAPE	(Wang et al., 2009)

Table 4 Results for RQ3

Due to globalization, outsourcing, IT, and increased integration requirements, companies now have limitations on output measurement, monitoring, and decision making. These new factors have motivated developing new insights into management functions within the business environment with adequate performance measures and metrics to enhance the overall supply chain operations (Balfaqih et al., 2016).

- *Supply chain performance*

A total of six metrics techniques and a framework have corresponded to the performance measurement techniques to measure the overall supply chain performance and AI/ML techniques. (Bhagwat & Sharma, 2009) have proposed the integrated analytical hierarchy process (AHP) and pre-emptive goal programming (PGP) model to identify the most critical performance measures and metrics to optimize the overall supply chain operations. Whereas (Trivedi & Rajesh, 2013) have emphasized using the AHP analysis to select the most important KPIs to help a business evaluate the supply chain performance. According to (Balfaqih et al., 2016), Both AHP and analytic network processes (ANP) are qualitative multi-attribute decision methodologies that provide structured communications to address a wide range of performance measurements. (Drzymalski et al. 2010) have proposed to measure SC efficiency based on an intra-organizational and inter-organizations context by applying both AHP- and ANP techniques features. The data envelopment analysis model (DEA) is a valuable tool for evaluating organizations with multiple inputs and outputs, and it considers both qualitative and quantitative measures (Balfaqih et al., 2016). (Wong & Wong, 2007) have developed the tool using the DEA model to measure the internal supply chain efficiency under uncertain environmental changes to identify inefficient operations and take the right decisions for enhancement.

- *S&OP*

A framework based on a set of criteria relating to appropriate measures such as completeness, internal process efficiency, horizontal or vertical integration, internal comparability, and usefulness has been developed by (Hulthén et al., 2016) to measure S&OP's performance. The framework helps to make practical suggestions for organizations during the development of efficiency improvement measures. It would also assist organizations in standardizing measures and increasing accountability.

- *AI/ML*

AI/ML has been widely used in various industries, including banking, marketing, healthcare. It is necessary to assess the effect and benefits of AI/ML strategies by measuring their performance. (Wang et al., 2009) have proposed the four quantitative statistical performance evaluation measures: Coefficient of correlation (R), Nash–Sutcliffe efficiency coefficient (E), Root mean squared error (RMSE), Mean absolute percentage error (MAPE) to help measure the performance of several AI/ML methods, which include autoregressive moving-average (ARMA) models, artificial neural network (ANN), adaptive neural-based fuzzy inference system (ANFIS) techniques, genetic programming (GP) models, and support vector machine (SVM) method.

2.5.4 According to the published literature, which capabilities are essential for implementing AI/ML technologies in supply chain operations?

The results for the RQ4, as shown in Table 5, presents the essential capabilities required for improving the supply chain operations efficiently and implementing AI/ML technologies in the supply chain operations effectively.

Capabilities	Description	Sources
Resilience Capability	Resilience is the capability to respond to unexpected disturbances and disruptions in the supply chain operations	(Yu et al., 2019)
Dynamic and agile capabilities	Helps to develop abilities to achieve strategic advantages in highly changing and dynamic environments	(Rasouli et al., 2015), (Masteikaa, 2015), (Asabe et al., 2020)
Absorptive capability	Enables recognition and utilization of relevant knowledge to improve the collaborative process over time	(Zacharia et al., 2011)
collaborative process competence capability	Enables the process of sharing relevant information, managing conflict, assessing options, jointly making decisions, and combining resources to accomplish objectives collaboratively.	(Zacharia et al., 2011)
Management capabilities	Enables to smoothly manage the complexities in all fields of supply chain operations.	(Gunasekaran et al., 2017)
Big data capabilities	effectively leveraging a resource such as big data can lead to significant profit	(Yu et al., 2018)
Data management and analytics capabilities	It helps access accurate information, manage the critical portion of the data, and provide data integration as a single source for applying relevant analytics techniques.	(Hua et al., 2015)
Performance measurement capabilities	Helps to evaluate the overall supply chain operations, decision making, and customer satisfaction	(Thakkar, 2011)

Table 5 Results for RQ4

Capabilities are broadly defined as complex bundles of skills and accumulated knowledge that enable firms to coordinate activities and use their assets (Yu et al., 2018). According to (Rajaguru & Jekanyika, 2013), supply chain capability refers to an organization's ability to identify, use, and assimilate internal and external resources and information to facilitate entire supply chain activities. In total, nine capabilities were reported to be more suitable in the supply chain operations when implementing the new innovative technologies for the best performance of the supply chain. In response to changing market conditions and technologies, supply chains are becoming more dynamic, making handling the flow of materials more complex and increasing the risk of disruption. Firms can focus on developing resilience capabilities to mitigate the negative impact of disorders to survive in an increasingly unpredictable market environment. (Yu et al., 2019) have stated that supply chain resilience capability is an adaptive capability of the supply chain to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function. (Rasouli et al., 2015) have proposed dynamic capabilities as enabling the supply chain management to sense the changes in the environment and rapidly respond to the changes. They have focused on three dynamic capability dimensions: digital options, agility, and entrepreneurial alertness.

Digital options focus on a set of IT-enabled capabilities that are based on process-oriented and knowledge-oriented information systems. Entrepreneurial alertness is the ability of a system to explore its marketplace through preexisting knowledge and proactive experiments to detect an opportunity and act accordingly. Agility is the ability to spot opportunities for innovation and seize them by gathering the necessary tools. Customer agility, collaborating agility, and operational agility are three interconnected capabilities. Whereas (Masteikaa 2015) defined dynamic capability as fulfilling the targets under uncertain conditions by developing and modifying the resources. Compared to (Rasouli et al., 2015), (Masteikaa 2015) focuses on three different dimensions: Sensing, Seizing, and Reconfiguring.

On the other hand (Asabe et al., 2020) have emphasized agile capabilities, which help maximize the transformation of sustainability practices into environmental and social sustainability performance. Implementing agile capabilities in the organization will help in knowledge management, strong leadership commitment, organization learning, organizational culture, multidisciplinary teams, decentralized decision-making, customer and stakeholder involvement. Collaboration plays a vital role in boosting firms' core competencies and strategic capabilities in today's dynamic environment. Collaboration with suppliers, customers, and even competitors to co-create solutions to problems is increasingly vital to a firm's business strategy and a source of competitive advantage. (Zacharia et al., 2011) defined collaboration as a mechanism to combine and deploy external and internal knowledge and skills, and examined two capabilities: absorptive capacity and collaboration process competence, which influence such collaborations' operational and relational outcomes.

The absorptive capability enables recognizing and taking advantage of new ideas, willingness to adopt new ideas and adapt to change, and commitment to create an environment that encourages new ideas. When organizations can access new ideas and adjust, they are more likely to invest time and resources to engage with external firms in anticipation that there is a significant return on that investment. In a dynamically evolving world, collaborative process competence allows businesses to determine what information they need to obtain from others and what knowledge they must possess. Instead of acquiring knowledge (learning) from a partner and solving a problem unilaterally, a firm can collaborate in a joint problem-solving process to access a partner's knowledge stock and apply the combined knowledge to leverage complementarities. Collaborative process competence capability helps manage the collaboration process, from partner and participant selection to facilitation of knowledge exchange and synthesis, to monitoring and adjusting the process for timely and successful completion.

Managing a dynamic supply chain with complexities would be a challenging task for the supply chain stakeholders. Supply chain management faces many challenges, such as globalization, increasing logistics cost, greater product variety, shorter product life cycles, increased level of risk, increased labor costs in developing countries, the rapid development of information technology, sustainability, and volatility of commodity prices. These challenges require capable workers with dynamic skills to make the supply chains of the future successful. Each activity requires a different skill set to manage the supply chain operations. (Gunasekaran et al., 2017) proposed for smooth management of the overall supply chain operations. Firms need to develop complexity management capability, Information systems capability, supply chain knowledge management capability, relationship management within process capabilities, performance measurement capability, risk management capabilities, and /talent management capabilities. Large volumes of data from different sources and constructs accumulate at an increasing pace of supply chain operations. It is critical to handle big data with more efficient and effective capabilities to gain a competitive edge in finance, processes, and planning. (Yu et al., 2018) proposed four main capabilities required to manage the big data. Information exchange capability, Interfirm coordination capability, Activity integration capability, and Supply chain responsiveness capability. Effectively leveraging a resource such as big data with four main capabilities can lead to significant profit.

On the other hand, (Hua et al., 2015) have suggested that getting the most out of the big data analyzing capabilities and interpreting data capabilities are essential for the best performance of the supply chain. Analyzing capabilities contain predictive analytics, data mining, case-based reasoning, exploratory data analysis, business intelligence, and machine learning techniques that could help firms mine the unstructured data, i.e., understand customers' preferences and needs. It is essential to measure the performance of the firms to make decisions, plan the process, and customer satisfaction. (Thakkar, 2011) has proposed the performance measurement capability to capture the essence of organizational performance.

2.6 Discussion

The SLR results indicate that many AI technologies have been implemented at every supply-china operation level. Due to globalization and increasing complexities, the supply chain continues to evolve in a fiercely competitive economy. In today's world supply chain is becoming more information-intensive, and its focus has been directed toward adopting the new innovative artificial intelligence and machine learning technologies at each level (e.g., inventory, demand, and supply forecasting, transportation, procurement, and operations planning) (Toorajipour et al., 2021). When analyzing the papers about the application of AI/ML in the supply chain operation and S&OP, the results encountered that AI-related research has increased over the years. The present findings are restricted to the supply chain fields and S&OP due to the intention of this analysis to explore the correlation between AI and supply chain operation and planning using related keywords. According to Table 2, AI/ML technologies have been used in various sub-fields of the supply chain, including demand and sales planning, inventory replenishment, production monitoring, inbound and outbound logistics, supply chain risk management, and integrated business planning. The common factor of these sub-fields of the supply chains is their need for a decision-making mechanism justifying their interaction with the various AI algorithms. Increasing support for decision-making is being provided by data processing, data trend detection, forecasting, and anticipation by artificial intelligence and machine learning technology.

Table 2 indicates that seven articles have been emphasized the AI/ML application related to forecasting. Accurate forecasting is one of the most promising applications of AI/ML in the supply chain. Precise forecasting in the supply chain operations helps make a correct decision and maximize the company's overall profitability (Efendigil et al., 2009). To our surprise, there is a significant growth in adopting AI/ML technologies in forecasting and production planning, inventory management, and logistics management. The findings suggest that the application of AI/ML technologies helps the supply chain create a fully automated and self-adjusted decision-making system. AI-powered supply chain management enables businesses to predict demand spikes and adjust the routes and volumes of material flows. When all the articles were analyzed to find the AI/ML application in supply chain operation and S&OP, there is limited evidence on prescribing the methods to implement the AI/ML technologies and required capabilities to adopt the AI/ML technologies. S&OP is categorized as part of the supply chain management and supply chain planning paradigms. The results indicated a lack of evidence on how AI/ML technologies have an impact on S&OP. As suggested by (Schlegel et al., 2020), implementing Big Data analysis enable advanced business forecasting and the S&OP aspects to evolve in line with the prevalent maturity, such as meetings and partnership, organization, success measures, and IT.

The outcome of Table 3 denotes that the approach of AI/ML technologies to tackle supply chain and operations planning problems. ANN is the most prevalent technique that strongly impacts producing the accurate demand and supply forecast under high volatile market demand planning issues. (Gallego-

García & García-García, 2021), (Amirkolaii et al., 2017) suggested that ANN be a suitable technique for decision-making and operations planning more precisely under uncertain demand and market fluctuation scenarios. (Choy et al., 2004) designed an intelligent supplier relationship management using the ANN technique to avoid delaying selecting the suppliers during new product development. ANN techniques are limited to forecasting and decision-making and are applied in production monitoring and transportation services. Fuzzy models' second most prevalent technique is to make an innovative segmentation approach that combines cluster analyses and fuzzy learning techniques to produce higher accuracy in measuring and evaluating organization performance. In a complex organizational environment, it has been challenging to measure and evaluate the coordination between the supply chain partners in terms of their coordination, contract agreement, communication, information sharing, and use of information technologies (Arshinder et al., 2007) suggested Fuzzy logic approach is the most suitable to tackle this challenge. The support vector machine (SVM) and machine learning in combination with neuro networks also have a significant impact in generating accurate forecasts in an uncertain and rapidly changing market and demand of the product (Feizabadi, 2020) (Gecevska, 2017). Apart from ANN, SVM, ML, and Fuzzy logic (Hnaien et al., 2009) suggested a genetic algorithm (GA) for Supply planning under lead time uncertainties for two-level assembly systems. In the production area, to tackle the problems like monitoring and managing various changes and uncertainty in manufacturing processes, the agent-based system is a good approach (Monostori, 2003). Overall, the findings signify that the application of AI/ML has contributed to tackling the issues in the supply chain. The results show that there is a lack of significance on data management in terms of data extraction from a specific system, types of data needed from the analysis, the method for incorporating databases with AI/ML software, and data governance, which is essential in sharing data from inter-organizational systems.

To our surprise, findings from Table 4 indicates that there are established techniques, methodologies, and tools to identify the most critical performance measures and metrics of the supply chain performance, to select essential KPIs and methods that provide structured communications to address a wide range of performance measurements, optimize the overall supply chain, and to evaluate the business operations. An interesting finding was from (Bhagwat & Sharma, 2009) and (Trivedi & Rajesh, 2013). They have proposed an analytical hierarchy process (AHP) and analytic network process (ANP) models to select the critical KPIs and performance measurement and metrics of the supply chain operations. Whereas (Wong & Wong, 2007) developed a tool using the data envelopment analysis (DEA) technique to identify inefficient operations and make the right decisions for enhancement. The framework for measuring the performance of S&OP proposed by (Hulthén et al., 2016) is based on a set of standards for suitable measures such as comprehensiveness, internal process performance, horizontal and vertical integration, internal comparability, and usefulness, which aid in the development of specific recommendations for companies while designing measures to improve process effectiveness and efficiency. It would also assist organizations in standardizing measures and increasing accountability. Four quantitative standard statistical performance evaluation measures have been reported for measuring the application efficiency of AI/ML technologies. Coefficient of correlation (R), Nash–Sutcliffe efficiency coefficient (E), Root mean squared error (RMSE), and mean absolute percentage error (MAPE) to measure the performance of several AI/ML methods, which include autoregressive moving-average (ARMA) models, artificial neural network (ANN), adaptive neural-based fuzzy inference system (ANFIS) techniques, genetic programming (GP) models, and support vector machine (SVM) method have been encountered. The results indicate that there has been evolution and implementation of tools and techniques to measure supply chain performance, AI/ML, and S&OP individually from the analysis of the results. There is lack of focus on metrics to assess the application of AI/ML in the process of the supply chain operations and S&OP.

The results from Table 5 indicate that the crucial capabilities are essential for the smooth operations of the supply chain, especially when planning to implement new innovative technologies in supply chain operations. Managing the supply chain with satisfactory outcomes under uncertainty in the environmental changes, fluctuating customer demands, and managerial issues is complex. To overcome the complexities in the supply chain, organizations have to develop the appropriate capabilities. Dynamic and agile capabilities help to develop abilities to achieve strategic advantages in highly changing and dynamic environments. Every organization must have the dynamic capability to cope with highly changing and dynamic environments (Rasouli et al., 2015). For resilience in the organization under unexpected disturbances and disruptions in the organization's supply chain operations, resilience capability was best suited for the organization (Yu et al., 2019). As supply chain operations are data-driven and interrelated with other business operations collaboration, management capabilities play an essential role in managing the complexities in all fields of supply chain operations (Zacharia et al., 2011) (Gunasekaran et al., 2017). The results were surprising because they concentrate on dynamic, resilience, and management capabilities as well as on data management, analytical, and performance measurement capabilities. Data management and analytical capabilities help the organization access accurate information, manage the critical portion of the data, and provide data integration as a single source for applying relevant analytics techniques (Hua et al., 2015). These capabilities are reported to essential capabilities when managing the large amount of data generated from various systems and sources to capture the insights and make optimal decisions. Tracking the overall supply chain's performance is essential for making decisions to improve supply chain efficiency. For this reason, performance measurement capability needed to be incorporated in organizations that help the organization evaluate the overall performance (Thakkar, 2011). Overall, the reported capabilities are essential for the organization when planning to implement new innovative technologies and cope with disruptions in the supply chain operations.

3. DESIGN

This chapter presents the proposed framework for developing the data management, analytical, and performance management capabilities in the supply chain organization. Developing these capabilities can help supply chain organizations improve data governance and data quality, make more informed decisions about investing in and selecting appropriate AI/ML technologies in supply chain fields and enhance supply chain performance management. The development and implementation of this capability framework depend on the supply chain organizations. For example, if the organizations already have a well-defined data governance structure and high-scale data quality improvement processes, they can focus on developing analytical and performance management capabilities. On the other hand, if the organizations are at the initial phase of implementing an AI/ML technology-driven supply chain, in this case, the organizations can follow to develop data management, analytical, and performance management capabilities sequentially, as presented in Figure 3. The sections that follow after this will provide a comprehensive explanation of each step constituting the framework.

In the initial phase, the application of the framework in the organization should begin with developing data management capability before adopting the most appropriate AI/ML technologies in the supply chain fields. For maximum benefits of the AI/ML technologies in the supply chain, high data quality needs to be generated for accurate results from analysis using suitable AI/ML technologies. High the data quality, the more precise outcome will be generated. Therefore, firstly the organization needs to focus on developing data management capability, which helps in improving the data quality and defining the data governance structure. Second, the organizations should focus on developing analytical capability, which assists in adopting the most appropriate AI/ML techniques in the supply chain fields for operations excellence. In the third step, the organizations need to develop performance management capability to monitor and manage the supply chain's performance by implementing the Six Sigma methodology and developing the Key Performance Indicators (KPIs) dashboard. Developing the performance management capability assists in tracking the supply chain operations' performance, helps in monitoring and evaluating the performance, and making decisions efficiently.

This research aims to design the framework to develop data management capabilities for improving data governance and quality by following the correct steps, analytical capability for choosing and implementing appropriate AI/ML technologies for the specific fields of the supply chain. Furthermore, the performance management capability to develop a dashboard for monitoring and managing the performance of the supply chain. This approach aims at guiding organizations to be prepared efficiently for adopting AI/ML technologies and managing the supply chain effectively.

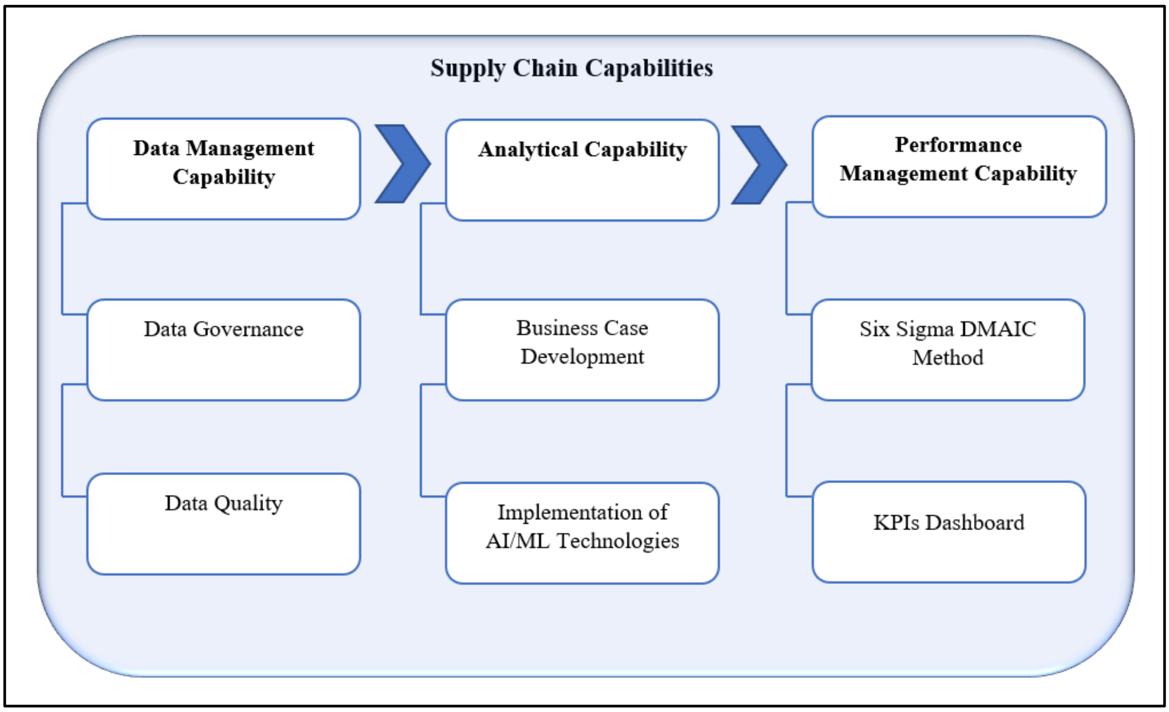

Figure 3 Supply Chain Capability Development Framework

3.1 Data management capability

Today's supply chain operations are inundated with data, motivating new ways of thinking about how data are produced, organized, and analyzed. It has provided an impetus for organizations to adopt the best AI/ML technologies to enhance supply chain operations and ultimately helps in measuring the supply chain performance and decision-making process. Large volumes of data are being collected at an increasing rate of supply chain operations from various forms and constructs ranging from GPS data to allow dynamic routing and scheduling of deliveries, point of sales (POS) data, warehouse operational data, production line data, inventory data, and several other forms of structured and unstructured data from numerous parties across the entire supply chain (Rowe & PournaderM, 2017).

Data management is the backbone of supply chain operations. The primary goal of big data is to improve supply chain maturity by maintaining data accuracy and increasing visibility and control throughout the supply chain in order to maximize agility and responsiveness. Despite the potential benefits of big data, companies cannot harness the power of available data to generate valuable insights for their businesses. As reported by (Rowe & PournaderM, 2017), the underlining reasons are due to the supply chain's lacking data management capabilities. In the first step, as per Figure 3, the organization should focus on Data Governance and Data quality components which are essential for developing data management capabilities. Data governance plays a valuable role in defining processes, policies, standards, organization, and technologies required to manage and ensure the availability, accessibility, quality, consistency, and security of data in an organization (Panian, 2010). The data quality is the pre-processing stage that helps high volume, variety, velocity, veracity, value raw data in cleaning as much as possible, applying noise filters to remove the bad quality of data and sub-processes for integration and filtering data for transformation/normalization. We will discuss these two components (data governance and data quality) in more detail in the following sections.

3.1.1 Data Governance

In order to address data quality issues as a first step in the data management capability, organizations need to adopt a holistic approach, focusing on "people, processes, and technology," and organizations need to constantly quantify and measure their data quality (Friedman, 2014). This implies that data must be governed in order to address data quality issues. The technology, as well as people, drive the data governance.

There are various definitions of data governance. (Cheong & Chang, 2007) defines data governance as the process by which a company manages quantity, consistency, usability, security, and data availability. (Panian, 2010) define data governance as the collection of decision rights, processes, standards, policies, and technologies required to manage, maintain and exploit information as an enterprise resource. Whereas (Wende, 2007) states that data governance refers to the administrative bodies, rules, decision rights, and accountabilities of people and information systems as they perform information-related processes. Data governance is essential in light of the definitions above because it defines policies and procedures to ensure proactive and effective data management. Data governance facilitates cooperation from different levels of an organization to handle enterprise-wide data and the ability to align various data-related initiatives with organizational goals.

To enhance the overall value of the data as an asset to the organization. Organizations need to implement four critical components for governing data, which helps establish the data characteristics for accessing data efficiently and securely. As mentioned in Table 6, the key components are Standards, Policies and Processes, Organization, and Technology (Panian, 2010).

Components	Description
Standards	The establishment of data standards in an organization is a core function of data governance. Organizations should create data definitions and taxonomies. Enterprise data models must be developed, technical requirements and data development must be enforced.
Policies and Processes	The foundation of an effective data governance practice is achieved by establishing and enforcing policies and processes around the creation, development, control, management, and audit of data. Supply chain organizations need to define data and data-related business rules, control access to and deliver data, establish ongoing monitoring and measurement mechanisms, and manage data changes.
Organization	When launching a data governance initiative, organizations need to design and aggress the organizational structure. Organizations need to define the roles and responsibilities within the organization that is accountable for the data. The organization may include various positions at different levels, involving both business and IT personnel - from executive councils to day-to-day implementers, such as data stewards and data analysts. For successful data governance, the organizations should address training and organizational change management issues.
Technology	Organizations should implement advanced technologies to automate and scale the development and enforcement of data governance standards, policies, and processes. Organizations can rely on a data integration infrastructure architecture with built-in tools for accessing, filtering, transforming, delivering, and monitoring data.

Table 6 Data Governance Components

Implementing the core components of data governance allows the enterprise to maintain and establish key data characteristics, thus increasing the data's total value as an asset to the organization. Data accessibility, data availability, data quality, data consistency, data auditability, and data security are the six main characteristics presented in Figure 4.

- Accessibility: Ensuring that all enterprise data can be accessed, regardless of their source or structure.
- Availability: Ensuring that data are available to users and applications, when, where, and how it is needed.
- Quality: Ensuring the completeness, accuracy, and integrity of data.
- Consistency: Ensuring the meaning of data is consistent and reconciled across all systems, processes, and organizational units.
- Auditability: Ensuring there are controls and an audit trail on the data.
- Security: Ensuring secure access to the data.

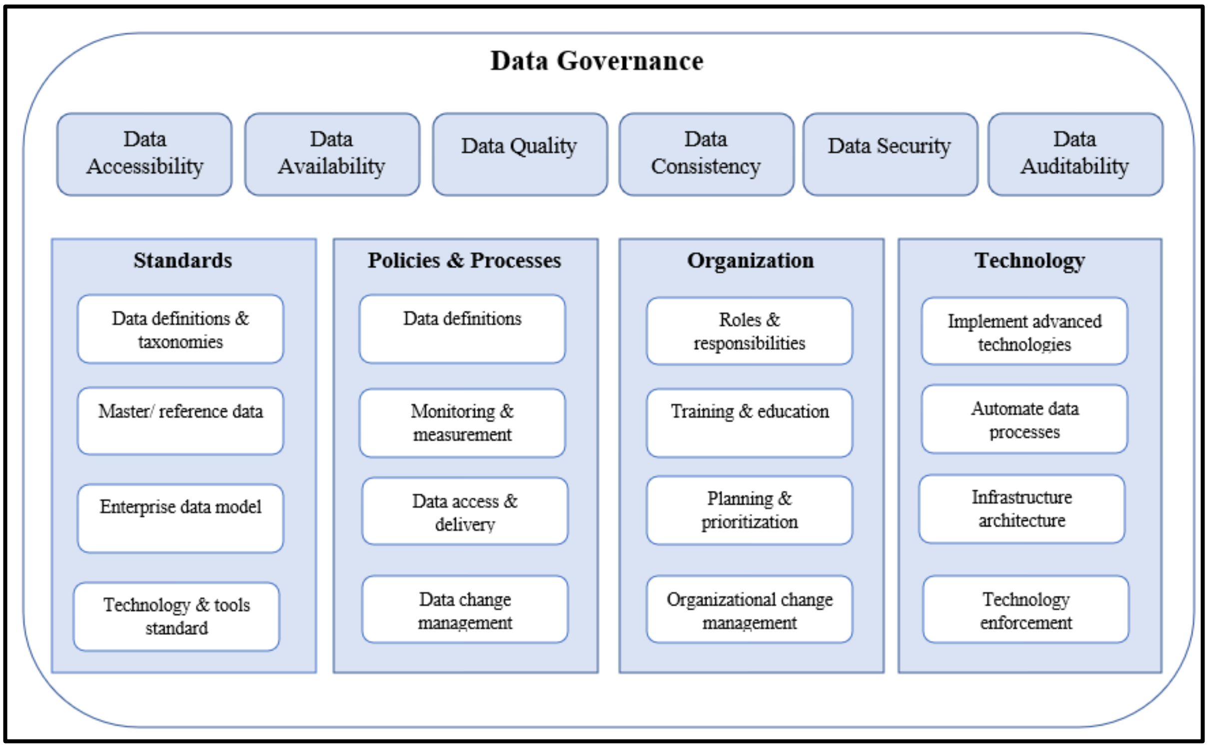

Figure 4 Data Governance

To successfully implement the data governance strategies, the organization should correctly assign the responsibilities to the stakeholders with appropriate backgrounds and experience. As previously stated, a collaboration between people is critical for initiating data governance methods. Individuals with designated roles such as Chief Data Officers, Data Stewards, Owners, and Operators can assist in strategically managing and defining data governance. They can also assist in establishing standards, business requirements, data quality improvement, and help business departments achieve their data objectives (Wende, 2007).

3.1.2 Data quality

The quality of Big Data is of great relevance and importance. Organizations need to focus on improving the raw quality of the data in the pre-processing stage. As previously stated, the high quality of the data increased the accurate analysis outputs. In the following step, organizations should focus on processing the raw data generated from various sources in the supply chain operations and aim to achieve a high quality of data for accurate analysis.

In the pre-processing step, organizations should implement and process the raw data in three main stages Activity selection stage, the Techniques selection stage, and the Data quality stage. There are several data techniques and rules to improve data quality in each activity of the pre-processing phase. This research aims to propose the sequential method for the acquisition of data.

Large volumes of raw data accelerated in the supply chain operations in many forms and structures from GPS to dynamic delivery routing and scheduling, sales point (POS) data, warehouses operational data, production line data, inventory data, and several forms of structuring and unstructured data from several supply parties. These data must be filtered and cleaned, reformatted and structured, deducted, extracted, and compressed illegal values. As shown in Figure 5, are the pre-processing steps that are essential to convert the data into levels that are appropriate or useful for analysis (Juneja & Das, 2019).

For pre-processing the data, as recommended by (Taleb et al., 2015), the organizations should perform six sub-processes as mentioned below to enhance the data quality.

- Data integration – As data is accumulated and generated from multiple sources in various forms, structured/semi-structured/unstructured, varying formats, junk. Data from all these sources need to combine and provide users with a unified view of the data and provide coherent storage.
- Data Enhancements and Enrichment – When consolidating data, the organization should define the processes for increasing the value of a pool of additional data collected from other supporting sources to produce fused data enriched with more knowledge and potentially improved qualitatively.
- Data transformation – In this step, the organization should initiate the data transformation, which involves many steps or sub-processes like capturing or pulling data from multiple sources. Data may need to be reformatted, normalized, aggregated, even migrated from a system to another.
- Data reduction – Organizations should focus on reducing the amount of data so that it becomes non-redundant. This helps increase the data storage efficiency and reduce costs by removing data that is not important and retaining only the significant parts for that particular work/task.
- Data discretization – The range of a continuous attribute should be extracted and segregated into intervals by the organizations so that it can be used effectively within existing mining algorithms and techniques.
- Data Cleansing – This process helps to improve the inaccurate, incomplete, or irrelevant data from the data acquired so that it can be processed and analyzed to extract beneficial value from it. As proposed by (Taleb et al., 2015), organizations can implement several methodologies like statistical, clustering, pattern-based, parsing, association rules, and methods used for outliers identification for the data cleaning process.

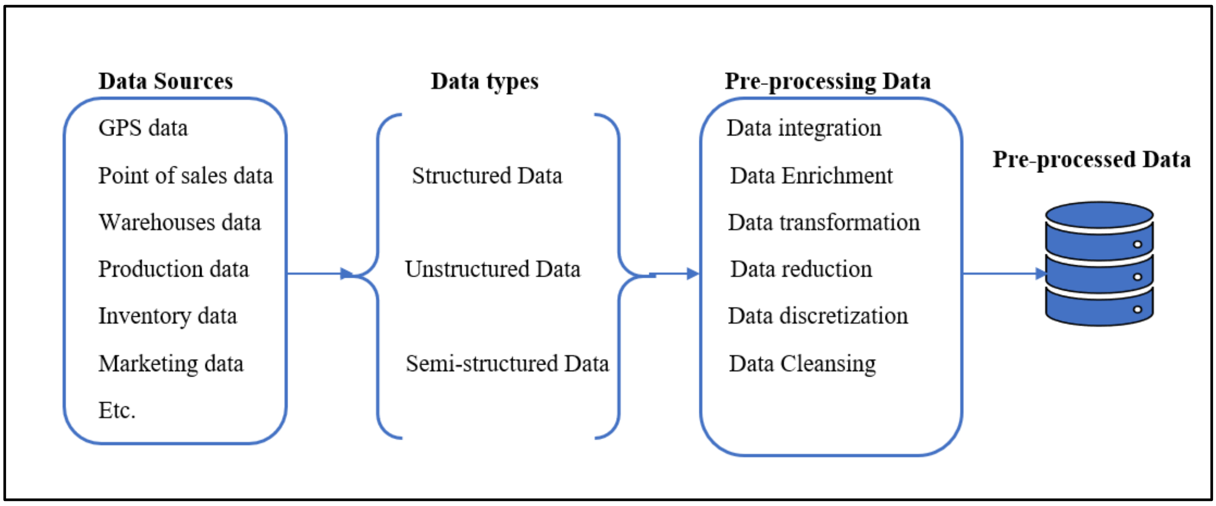

Figure 5 Pre-Processing Data

After processing the data, it is crucial to measure the quality of the data and store it in secure databases which can be accessible for analysis. The data owners, managers, and operators can be responsible stakeholders for measuring the quality of data. According to (Glowalla et al., 2014), the data quality measurement dimensions are listed below in Table 7.

Data quality dimensions	Description
Accuracy	Determines whether data are recorded accurately and adequately reflect actual values.
Timeliness	Determines whether or not data is accurate. Data currency and volatility are two terms that are often used.
Consistency	Determines whether successfully conveys the format and structure. Conditional functional dependencies are defined in some Big Data Quality works as data quality rules for detecting and capturing semantic errors.
Completeness	This metric determines whether all related data has been registered with no missed entries or values.

Table 7 Data Quality Dimensions

3.2 Analytical Capability

The supply chain can be viewed as a series of four key processes: plan, source, make, and delivery, as shown in Figure 6 (Stewart, 1997). These four processes play crucial roles in streamlining supply chain operations and boosting overall business efficiency (Li et al., 2011). There is a lot of potential in integrating analytical techniques and IT tools into those four processes (Trkman et al., 2010). To manage supply chain operations, organizations must have analytical capabilities. Adopting the analytical capabilities in the supply chain organizations can help to automate, augment and enhance customer experience and decision-making, and reinvent company strategies. Innovative analytical technology can support demand forecasts in a critical environment, improve supply and inventory management and, most importantly, allow organizations to make decisions and provide opportunities for optimizing the supply chain in a competitive world.

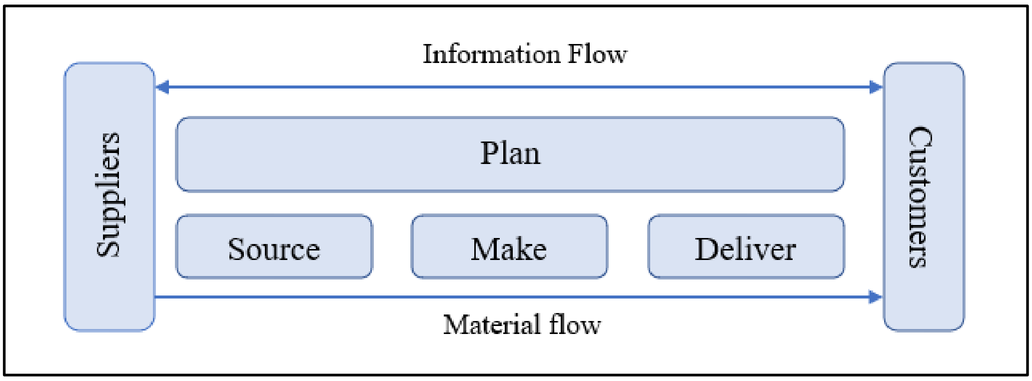

Figure 6 Supply chain processes

In the second step of capability development, as per Figure 3, organizations need to focus on planning and implementing the most appropriate AI/ML technologies for the four key supply chain processes presented in Figure 6. Once the quality of data is managed and improved, organizations can unlock their data capability to use the data more effectively and effectively through analytical techniques. Several analytical techniques can be implemented in supply chain operations, but this research focuses on predictive analytics and proposes AI/ML technologies in all supply chain processes. As stated, many AI/ML technologies have been enhancing at every level of the supply chain operations to overcome environmental and business challenges. Organizations must concentrate on management, infrastructure, and financial investment planning before selecting and integrating AI/ML solutions in the supply chain process.

3.2.1 DEVELOP THE BUSINESS CASE FOR AI/ML IMPLEMENTATION

Implementing new IT technology in the enterprise without first calculating the costs, benefits, and risks will result in a major project failure and have a negative impact on the company (David et al., 2002). Therefore, developing a business case for incorporating AI/ML technology in an enterprise will aid in determining the overall cost of ownership, various categories of benefits, identifying risks, and determining how to mitigate those risks (Ward et al., 2007).

This research aims to propose the approach of business case development as suggested by (Ward et al., 2007) be used as a component in our framework (Figure 3). They've proposed a framework for structuring the benefits, costs, and risks. The proposed process has six steps for developing a more specific and reliable business case. According to (Ward et al., 2007), the business case model is intended to help organizations measure costs, benefits, and risk and establish priorities for different investments for capital and resources. It also supports identifying each benefit seen in the combination of IT and business transformations, a benefits realization plan, and commitments. Developing a business case can help supply chain organizations make choices on goals and whether or not to incorporate new innovative technology and build decision-making capability. As mentioned in Table 8, organizations need to focus on the six steps when developing the business case for implementing AI/ML technologies.

Step Sr.	Steps for developing the business case
1	**Define Business Drivers and Investment Objectives** A compelling and robust business case should start with a statement of the organization's existing challenges that need to be resolved – the business drivers. Senior managers and those in the company would be well suited to identifying problems and inventing solutions. The business case should then state precisely what investment the company aims to accomplish, which would be the investment goals.
2	**Identify Benefits, Measures, and Owners** After defining the drivers and agreed-upon investment objectives, the organizations should identify the expected benefits if the goals are met. After identifying the benefits, it is essential to measure the benefits and allocate the benefits owner.
3	**Structure the Benefits** The third step is to structure the benefits according to the proposed framework by (Ward et al., 2007), which can be found in appendix 1. The framework proposed aims to

	distinguish or structure the benefits by two factors: the form of company improvement which generates profit and the level of explicitness in the benefit before expenditure is made, which is understood or can be decided.
4	**Identify Organizational Changes enabling Benefits** The fourth step suggests using the framework to classify each anticipated benefit based on the primary form of improvement that would be required to achieve it.
5	**Determine the Explicit Value of each Benefit** Following the classification of each benefit, the fifth step proposes assigning a value to the benefit based on the knowledge that is either available or that can be obtained before the investment is made.
6	**Identify Costs and Risks** In addition to the benefits, the business case should also contain the costs and risks. In the final step, the company should determine the cost of assigning the project as well as the project's risks.

Table 8 Steps for developing a business case

3.2.2 AI/ML TECHNOLOGIES IN THE SUPPLY CHAIN OPERATIONS

The second step consists of choosing predictive analytical techniques like AI/ML in supply chain operations. Research suggests that AI/ML technologies drive the supply efficiently under uncertain conditions. The study's goal is to recommend various AI/ML technologies that may be deployed in four main supply chain processes: plan, source, make, and deliver, in order to address challenges in each field, as mentioned in Figure 6. Implementing the AI/ML technologies in the four key supply chain fields can enhance analytical capabilities.

- Analytical capability for planning:

The plan plays an important in gathering customer requirements, collecting information on available resources, and balancing requirements and resources to determine planned capabilities and resource gaps. Analytical techniques in the planning process focus on analyzing data to predict market trends of products and services and developing supply plans to match market demands (Trkman et al., 2010). Demand planning and supply planning are the critical roles performed in the planning process of the supply chain. Demand planning is an essential function. Thus, it aims to predict future demands, forecasting sales volumes, and profiling potential consumers accurately. At the same time, supply planning plays a crucial role in matching customer demands with resources profitably. Under highly uncertain and unpredictable demands and subsequent inaccurate forecasts, organizations are highly recommended to adopt the artificial neural network (ANN) technique to avoid the consequences of the inaccurate forecast (Gallego-García & García-García, 2021). For effective supply planning, fuzzy programming techniques can be implemented for supply planning efficiently.

- Analytical capability for sourcing:

The source process represents the identification and selection of sources of supply, scheduling deliveries and accepting receipt of products, and transfer of the product. The primary role of analytical techniques in the sourcing process is to improve inbound supply chain consolidation and optimization (Vegter et al., 2020). In addition, to avoid delay in selecting and evaluating the supplier when developing a new product and constraints in supplier relationship management. Therefore, AI/ML data mining techniques such as Support Vector Machine (SVM) and case-based neural network must be implemented by the organization, which helps to improve the supplier selection process, price negotiation, and supplier evaluation process (Gecevska, 2017). Adopting these advanced analytics can make the sourcing process intelligent and help to reduce the efforts in a detailed decision-making process.

- Analytical capability for Production:

The making process describes the activities associated with converting materials or creating the content for services. One of the most important activities is to ensure that each inventory item is produced correctly in terms of time, production belt, and batch (Vegter et al., 2020). Developing analytical capabilities in the making process can potentially play a role in various areas, such as predicting machinery failure, identifying anomalies in production processes, and discovering hidden patterns and potential problems. Predictive analytics techniques such as Genetic Algorithm (GA) are recommended in the manufacturing process to assist in different production-related planning challenges such as lot-sizing, lot-scheduling, and optimizing the sequence of orders in the manufacturing line (Hnaien et al., 2009). In addition, adopting clustering methods such as k-means and the agent-based system can help determine potential root causes of faults and processes, identify potential reasons for machine failures, and the impacts of such failures on production efficiency and product quality (Monostori, 2003).

- Analytical capability for delivering:

Delivery is the process associated with the creation, maintenance, and fulfillment of customer orders. It involves repetitive activities such as order creation, order batching, ship consolidation, carrier selection, and evaluation (Li et al., 2011). Adopting analytical capabilities in the delivery process improves the efficiency and effectiveness of outbound material by delivering products to customers and markets more efficiently. Order batching and scheduling the delivery are essential tasks in the distribution process. Therefore, organizations are suggested to implement a Genetic Algorithm-based model (GA) and fuzzy logic for designing logistics networks, delivery planning, vehicle routing, and assignments for delivering and scheduling on time and efficiently under uncertain environmental issues (Ren et al., 2020b). Adopting AI/ML techniques in the delivery process can enable organizations to manage orders and logistics intelligently.

Developing advanced analytical capabilities enables supply chain organizations to usher in a new era of supply chain optimization. It can automatically sift through large amounts of data to help an organization gain insight and extract value from the large amount of data associated with the procurement, processing, and distribution of goods. Most importantly, it improves forecasting, identifies inefficiencies, responds better to customer needs, drives innovation, and pursues breakthrough ideas. Simultaneously, organizations should establish a business case for using AI/ML technologies in the supply chain process, enabling them to make good decisions and invest financial resources efficiently.

3.3 Performance management capability

Firms have to analyze, monitor, and improve their existing supply chain management processes to beat market competition and stay competitive. For the efficient and high performance of the supply chain, organizations need to develop performance management capability (B. Chae, 2009). In this regard, the research proposes implementing a six sigma methodology and development of KPIs dashboard that enables the organization to review their existing supply chain management practices and guide them in making improvements. Six sigma focuses on reducing variation, measuring defects, and improving the quality of products, processes, and services. Six Sigma-based supply chain management effectively manages typical disruption issues in the supply chain. It ensures the delivery of the most appropriate product, at the right time, in the right place with the least cost to the customer (Knowles et al., 2005). The driving force of Six Sigma is defining, measuring, analyzing, improving, controlling (DMAIC) process used to structure individual projects. DMAIC is a data-driven quality strategy for improving operations and is an integral part of the Six Sigma methodology. In the third step, as per Figure 3, the organizations should focus on developing the capabilities to monitor and manage the performance of the supply chain. The performance management capabilities help the organizations analyze the overall processes and performance and enable managing a business as it provides the information necessary for decision-making and actions. In the following two sections, we elaborate on the Six Sigma DMAIC method and the dashboard, respectively

3.3.1 Six Sigma DMAIC method

Six sigma aims to define, analyze, correct, and improve the variables, which affect the quality of the supply chain process to decrease the number of defects and failures and propose the improvement means for the operations. Thus, six Sigma is a method of describing, measuring, analyzing, improving, and controlling (DMAIC) goods or processes that allows firms to deal with operational flaws and unpredictability (H. M. Yang et al., 2007).

DMAIC refers to Data-Driven Analysis and Improvement Cycle, and it is used to enhance, optimize, and stabilize business processes. For implementing the DMAIC method, organizations should follow the five-step method by applying appropriate DMAIC tools in each step. The five phases of the DMAIC as presented in Figure 7.

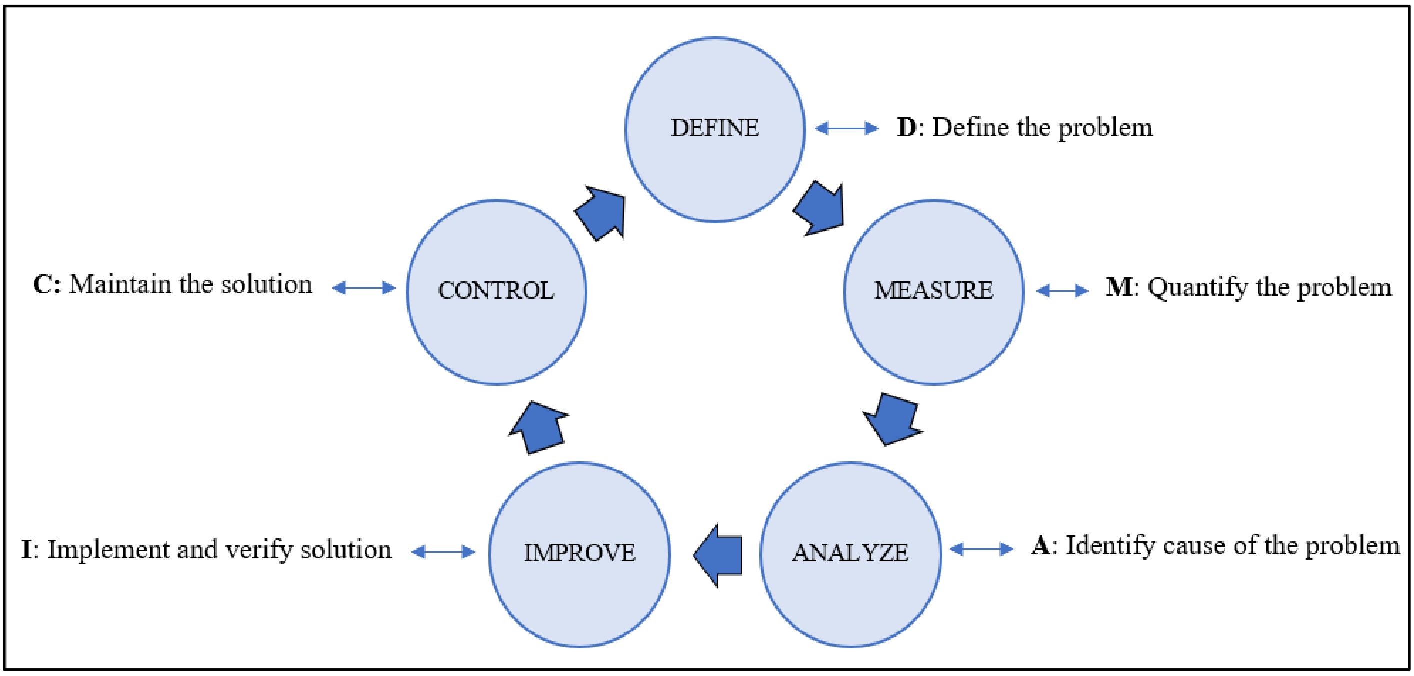

Figure 7 Six Sigma DMAIC

For managing the supply chain effectively and efficiently, organizations should implement the five steps of the six sigma DMAIC method with the suitable tool in each step, as mentioned in Table 9.

DMAIC	Description	Tools
D Define	In the define step, the organizations need to define the business problem, goal, potential resources, project scope, and high-level project timeline.	•Stakeholder analysis • VOC (voice of the customer) • High-level process map (SIPOC diagram)
M Measure	In the measuring step, the organizations should measure the specification of the problem/goal. This is a data collecting stage to establish process performance benchmarks. The baseline performance metrics from the Measure phase will be compared to the performance metric at the project's completion.	•Control charts •Data collection plan •Pareto chart •Value Stream Maps •Flow diagrams
A Analyze	In the analysis phase, the organizations need to identify, validate and select the root cause of business inefficiencies. Analysis of data helps to Identify gaps between current performance and goal performance prioritize opportunities to improve identify sources of variation.	• Control charts • Calculating sigma level • Stratification • Impact control matrix
I Improve	In the improve step, the organizations should test and implement a solution to the problem. Organizations should focus on Identifying creative solutions to eliminate the key root causes in order to fix and prevent process problems.	• Brainstorming • Solution matrix • Pilot study • Benchmarking
C Control	In the control step, the organizations should embed the changes and ensure sustainability. In this step; Amend ways of working, quantify and sign-off benefits, track improvement, officially close the project.	• Process control plan • Standardization • Quality control process chart • Control charts

Table 9 DMAIC method and tools

3.3.2 Supply chain KPIs Dashboard

Measuring or monitoring supply chain performance reveals the gap between planning and execution and helps companies identify potential problems and areas for improvement. Defining Key Performance Indicators (KPIs) enables organizations to determine and explain how the organizations are progressing to meet the business objectives. KPIs assist businesses in determining if the firm is on the right track and, if not, providing alerts to shift its focus. Developing KPIs for all the fields of supply chain operations (Plan. Source, Make, Deliver) offers the overall visibility of supply chain performance, reveals the gap planning and execution, and helps in identifying the correct potential problems (B. Chae, 2009).

Organizations should create KPI dashboards using data analysis and visualization platforms such as Tableau, Qlik, Power BI, and many. These technologies improve data visibility by producing straightforward graphics that compare current performance to historical trends and objectives, giving supply chain stakeholders the information they need to take focused action. As a result, enterprises can make better, more timely choices to create value for customers, shareholders, and diverse stakeholders across the supply chain using effective and responsive supply chain performance dashboards. When developing the KPI dashboard, the organizations should consider the key features and functionalities for effective monitoring mentioned in Table 10.

Sr. No.	KPI Dashboard Features
1	**Draw from real-time data, delivering real-time analytics** Use high-quality data with the help of data management capability. Ensure always focusing on the latest information by having dashboards interact directly in real-time with the source data, such as an ERP system.
2	**Customization for business and the specific KPIs** Prioritize the development of dashboards that are tied to the critical KPIs measured for the organization. Provide the features for customization of the dashboard according to the business owners and business process requirements.
3	**Self-service capability for “deep-dive” views** Dashboards should drill down to look into problem areas or fine-tune a query to have a different view. It should also correlate KPIs and generate the report from business and market perspectives to find the business process gap.

4	**Help drive decisions** Dashboard design should provide an easy read of key data, which the user is expected to analyze and make decisions. It should display the KPIs categorically for every month, quarter, and year with the target and actual results. It should also provide the KPI owner details.
5	**Shared view and accessible** The dashboard should not only display different shared views for business process owners, managers, and executives. Simultaneously, it should offer access within organizations as well as external supply chain partners, all while adhering to a security policy.

Table 10 KPI Dashboard Features

The organizations should develop the KPIs related to all processes of the supply chain operations. Developing leading KPIs for each field of the supply chain will enable organizations to effectively monitor the overall performance of the supply chain driven by AI/ML technologies. As mentioned in Table 11, these are the KPIs organizations should adopt while developing the KPI dashboard.

Planning	Forecast accuracy driven by AI/ML	For efficient production planning, material sourcing, and inventory management, an accurate forecast driven by AI/ML is essential. Forecast accuracy can be calculated by min. (number of sales) / max. (number of sales) per each product category.
	Total inventory days of supply	It aims to minimize the total amount spent on inventories within the supply chain network monthly. The general approach for calculation is to divide the currency value of total finished goods for a particular month by the daily average of costs of goods sold (the month’s costs of goods sold / 30 days).
	Cash-to-cash cycle time	It is used to estimate the financial efficiency of the supply chain. Cash-to-cash cycle time is the amount of time a company takes to recover its financial investment for purchasing. It is calculated as (inventory days + days of account receivable - days of account payable).
Source	Supplier fill rate	Supplier fill rate is the number of suppliers that have delivered orders on time as a percentage of total warehouse orders. It is calculated as (Fulfilled orders / Total orders) x 100.

	Procurement ROI	Procurement ROI is one of the essential measures for determining the cost-effectiveness and profitability of procurement investments. It is calculated as (Annual cost savings / Annual procurement cost).
Make	Manufacturing Lead Time	Manufacturing lead time refers to the time between placing an order and receiving the finished order from the manufacturer. It is calculated as (order delivery date - order received date).
	Production Attainment	The number of units made by the firm divided by the goal production output for a given period, expressed as a percentage, is known as production attainment. It assesses how well a firm achieves its manufacturing output targets. It is calculated as (total number of units manufactured by the company / target production output over a certain period of time).
	Percentage Maintenance Planned	Percentage Planned Maintenance is the maintenance metric that measures the number of planned maintenance tasks compared to all maintenance tasks. It is calculated as (# of planned maintenance hours ÷ # of total maintenance hours) × 100.
Delivery	On-time Delivery	The ratio of finished goods or shipments delivered on time to customers as a proportion of total units delivered or shipped is known as on-time delivery. It is an appropriate statistic for assuring customer satisfaction. It is calculated as (on time units / total units).
	Inventory Accuracy	Inventory Accuracy is a metric that assesses the differences between electronic records that represent inventory and the inventory's actual state. It is calculated as (number of counted items that perfectly match every aspect of the record / total number of items counted).
AI/ML	AI/ML Adoption	AI/ML Adoption is an internal measure to check the impact of the AI/ML technologies in the supply chain operations. It can be calculated as (% improvement of AI/ML adopted projects, compared to the % of unadopted AI/ML projects).

Table 11 Supply Chain KPIs

The roles and responsibilities of organizational members, units, or teams must be clearly defined and communicated enterprise-wide regularly for the suggested performance metrics to operate successfully, among other factors like systems, master data, and procedures (H. M. Yang et al., 2007).

In addition, each KPI's aiming level should be defined and updated regularly. Furthermore, the sales and operational planning (S&OP) team must be introduced to conduct the S&OP meeting (B. Chae, 2009). It is in charge of the complete supply chain, from demand forecasting through supply network architecture. This cross-functional group should play an essential role in performance measurement by monitoring the suggested metrics, determining the underlying causes of low-performing metrics, engaging with the units and individuals involved, and establishing continuous improvement and adaptation plans.

4. EVALUATION

This chapter presents the evaluation of the proposed framework. The evaluation process is an essential step in the DSRM as it evaluates the usefulness and impact of the framework when introduces in the supply chain organizations. The framework is evaluated by conducting interviews with three supply chain domain experts. The evaluation aims to determine the usefulness, feasibility, and impact of the proposed framework in supply chain operations.

4.1 EVALUATION PLAN

Three semi-structured interviews were conducted to evaluate the usefulness, feasibility, and effectiveness of the suggested framework. The semi-structured interviews were performed in accordance with the approach described in (Boyce. & Neale, 2006) for conducting in-depth interviews. They outline the six steps as follows:

Step 1 – Plan

Step 2 – Develop instruments

Step 3 – Train data collectors

Step 4 – Collect data

Step 5 – Analyze data

Step 6 – Disseminate findings

Steps 3 and 4 are not explicitly described in this chapter; nevertheless, the remaining steps are discussed in their sections. There is no need to train data collectors because the author conducts all interviews.

The interview aims to determine the usefulness, feasibility, and impact of the supply chain capability framework (Figure 3). Additionally, to identify any specific requirements or modifications that must be made within the organization prior to adopting the framework and evaluate whether the sequencing appears logical when applying the framework in organizations.

Due to COVID-19 measures, the evaluation interviews were conducted through video calls. Prior to the meeting, the primary set of evaluation questions was shared with the interviewers using Google Forms (Appendix 2) to enable them to respond, focusing on specific aspects of the framework. We used Microsoft PowerPoint to present the Supply Chain Capability Development Framework (Figure 3) during the interview session (Appendix3). The methodology, framework development process, and each element of the framework were explained in detail using PowerPoint slides for each expert.

Following the presentation of the artifact, semi-structured interviews were conducted to elicit responses to the questions listed in Table 12.

Seq. No.	Interview Questions
1	Do you find the framework is useful and relevant for supply chain organizations?
2	Is it feasible to adopt the framework in organizations?
3	In your view, do organizations need to fulfill any additional requirements before adopting the framework?
4	Does the sequencing appear logical when adopting the framework in an organization?
5	Based on your experience and perceptions, how much impact would the framework have if one implements it in the organizations?
6	Are there, in your view, any suboptimal aspects? Aspects that need improvement? For example, incomplete aspects?

Table 12 Interview Questions

4.2 Expert Panel

Three experts agreed to take part in the evaluation of the artifact.

Expert A.

Is a Senior SAP Consultant at IBM in Germany. With two years of professional experience in SAP technology. Being a senior SAP consultant at IBM, the responsibility is to discuss the potential solutions for business problems with different stakeholders. Evaluate costs and benefits and manage risks. Accompany the client from the as-is process analysis to the go-live of the newly implemented SAP functionalities.

Furthermore, act as a trusted expert for the client to help them overcome challenges that they face during the project execution. The job is focused on the supply chain areas of the SAP Software, covering areas like Material Management, Production Planning & Execution, Sales & Distribution. Additionally, focusing on covering different industries like Automotive, Industrial Products & Retail.

Expert B.

Is a Senior Application Architect in supply chain management at IBM in Germany. With ten years of professional experience in software architecture and design. Being a senior supply chain software architect at IBM, the responsibility is to deliver IT strategic roadmaps for Supply Chain, Merchandise Planning, Procurement, Inventory, Allocation, and Replenishment that are focused on technology capabilities for Business, Information, and Technology solutions. Collaborate with IT leaders and other domain architects to come up with forward-looking strategic and tactical plans.

Assist the clients in fulfilling their requirements and help in the execution of the project smoothly. In addition, coordinating with cross-functional teams and researching the latest developments in technology applicable to the supply chain enterprise.

Expert C

Is a Senor Project Manager and Data Governance Consultant in the Integrated Supply Chain team at Philips in Eindhoven. With nine years of professional experience in the supply chain domain. Being a project manager at Philips has responsible for driving performance management across Global ISC by defining KPIs and ensuring data quality, accuracy, and integrity of information stored in relevant systems, enabling a single source of truth through digitalization.

4.3 Evaluation Outcomes

This section will present the results of the semi-structured interviews. In the following section, each interview question will be discussed, and the respective answers of the interviewees will be summarized and presented.

4.3.1 Answers to interview questions

1. Do you find the framework is useful and relevant for supply chain organizations?

Expert A agrees with the overall strategy, stating that it is beneficial to have three distinct and essential pillars that address the critical issues that companies face. Interviewee finds the data management capability is a crucial element, as most of the problems occur with the data to support the business. Managing the data is key and very important in the long-term sustainability of the businesses. The expert determines that the data governance and data quality components are adequate for addressing obstacles such as not having available and accessible to all the legacy systems and databases within the organizations. As expert A finds, data management capability and the elements in the framework play a significant role. The expert feels that it is a crucial component for efficiently evaluating and addressing problems about the analytical capability. However, the expert believes that the analytical capability's execution and the practical outcome depend on data management. According to the interviewee, the performance management capability is also an important component since it allows to evaluate and monitor all supply chain activities on a daily basis, allowing for rapid resolution of issues and the ability to make effective decisions. Overall, Exper A believes that all framework elements are highly beneficial as guidelines for organizations.

Whereas expert B agrees that the framework will be more beneficial in light of the rapid growth of AI/ML technology adoption, and it should not be difficult to adapt and benefit (or at the very least sustain) a competitive edge. The expert believes that the framework presents the primary and most essential aspects since it may serve as a starting point for companies interested in implementing AI/ML technologies; moreover, it can establish a roadmap for the various teams within the supply chain organization.

On the other hand, expert C also finds the framework useful in supply chain organizations, especially while initiating the Sales and Operations Planning (S&OP) program. According to expert C, the framework can serve as a basis for improving efficiency and implementing new IT technologies in supply chain operations. It draws stakeholders' attention to the fundamental critical capabilities required for transforming from traditional to AI/ML-powered supply chain operations.

2. Is it feasible to adopt the framework in organizations?

According to expert A, feasibility in adopting the framework depends on the maturity of the organizations. For example, for multinational corporations with a large number of employees and businesses that already have a digital environment, implementing the framework would be complicated since it provides a broad view of the framework that would need more detailed steps for each element. However, adopting a framework by small businesses or startups may be feasible because it facilitates designating roles and serves as a suitable jumping-off point for transformation. On the other hand, the expert also feels that the data management part is the most challenging because some companies might not know what exactly needs to be done? Companies also might not be aware of what type of data they are collecting and have? Especially with the business case, organizations might not be aware of what they exactly need to achieve? Expert A believes that data management and business case development seem to be difficult when adopting the framework.

On the other hand, compared to expert A, expert B finds that the feasibility of adopting the framework depends on the organization's goals. According to the expert's opinion adopting the framework would mean investing for long-term benefits. Not all companies have the willingness and resources to invest in long-term goals.

Similarly, expert C believes that organizations may easily implement the framework. However, depending on the size and policies of the organization, the expert believes that performance management capabilities can be developed more conveniently than data management and analytical capabilities, as managing and governing data can be a complicated task in large organizations due to a large number of data sources and restricted access to data. Whereas, Implementing analytical technologies depends on the ambition level of the organizations.

3. In your view, do organizations need to fulfill any additional requirements before adopting the framework?

According to Expert A, companies must determine if AI/ML technologies are necessary for supply chain processes before implementing the framework. Implementing AI/ML technologies in organizations can be a complex task with heavy investments. The expert believes that, instead of AI/ML technologies, spreadsheets and basic software can solve the problems. So the expert suggests making efficient decisions is essential before planning to implement AI/ML technologies. On the other hand, the expert means being aware of organizational change, which could impact the daily work, after adopting AI/ML technologies by following the framework and recommends planning and managing the organizational changes and their impact on the day-to-day work efficiently.

According to expert B, before implementing the framework, businesses should evaluate what data they are generating and collected and what technical/analytical skilled resources they have within the company, which may help organizations make decisions and manage resources more efficiently. Expert C believes that organizations need to have significant IT infrastructure solutions before adopting the framework, and the connectivity between systems can be critical for success.

4. Does the sequencing appear logical when adopting the framework in an organization?

Because data is the key component and starting point, experts A, B, and C find the overall sequence in the proper order. According to expert A, if the data is not managed well, it can lead to a destructive impact on the analytical capabilities results and impact the organizations' performance management capability. However, the expert suggested discovering the cycling back process from the performance management to the data management through the DMAIC method, which helps to revert to the previous steps in case if missed any component to be adopted. As per expert B, not all companies would start at the beginning of the sequence. Most organizations already have their own data governance policies in place. Also, adopting the six sigma methodology and KPI dashboard might be already implemented in the supply chain industry. But in expert's opinion, the framework has flexibility in adopting as per the organizations' requirement. According to expert C, the sequence of the framework aids organizations to improve and adapt the technologies in the right directions at the initial phase. Overall, experts A, B, and C find the sequencing logical when adopting the framework in organizations.

5. Based on your experience and perceptions, how much impact would the framework have if one implements it in the organizations?

According to expert A, adopting the framework and following thoroughly can significantly benefit the organizations because it encompasses the overall aspects that must be present to adopt AI/ML technology in supply chain organizations effectively. Based on expert's experience, adopting the framework in organizations at the sub-tasks level would benefit more because it would help deliver the project's accurate and specific aspects, improving productivity and customer satisfaction. Overall, according to expert experience and perceptions, the framework can have a significant impact. Based on expert B's experience and perceptions, many supply chain organizations are unable to effectively leverage their data management capabilities and successfully implement AI/ML-driven process as expected. The framework can be an essential tool for the decision-makers and overcome the data management and implementation of AI/ML-driven process challenges in the organizations. According to expert B, the framework could have a significant impact on financial aspects as well as a considerable impact on the organization's performance. According to expert C, the framework can have a high impact on improving the operations of the supply chain, and it can benefit in making decisions efficiently by capturing focus on important elements of the framework. It can have a considerable impact on predictability improvement and operational excellence.

6. Are there, in your view, any suboptimal aspects? Aspects that need improvement? For example, incomplete aspects?

According to expert A, the Six Sigma DMAIC method is designed for industrial operations. It must be established that it is a suitable match for applying AI/ML technology. As suggested by the expert, the framework needs to have an organizational change management aspect because it is important for the organization to be resilient when adopting new methods, technologies, and frameworks. At the same time, expert B believes that the framework must have an internal assessment element before adopting the framework. This could help determine what type of data organizations are collecting and stored and also helps in analyzing what technical and analytical skilled resources organizations have, which would allow the organization to decide what parts of the frameworks to adapt. On the other hand, expert C recommends adding the IT infrastructure capabilities required to support the successful execution of data quality, essential IT tools for adopting AI/ML technologies, and developing KPIs dashboard.

4.4 REFLECTION

As part of the evaluation process, a reflection was made using the SWOT analysis method, which will help to review the strengths, weaknesses, opportunities, and threats of the designed artifact critically. The results are presented in the following Table 13:

<table>
<tr><th>Strengths</th><th>Weaknesses</th><th>Opportunities</th><th>Threats</th></tr>
<tr><td>The framework contains the necessary element for adopting AI/ML technologies</td><td>The framework represents a high-level approach. The framework's components provide a comprehensive view.</td><td>Adopting a framework can considerably benefit the organizations</td><td>The framework lacks dynamic and resilient capabilities, and as a result, it may not be able to endure unpredictable changes</td></tr>
<tr><td>The framework can be beneficial in the supply chain organization</td><td>The framework does not focus on change management capability</td><td>The framework can be adopted by any company willing for the digital transformation of the supply chain operations</td><td>Due to the framework's flexibility, it may mislead the company during implementation</td></tr>
<tr><td>Adoption of the framework is not complex</td><td>The framework does not present the iterative processes</td><td>The framework can increase productivity and add value to the organizations</td><td rowspan="2">The primary focus of the framework is limited to data management, analytical and performance management capabilities</td></tr>
<tr><td>The framework is flexible to adapt according to the organization's requirements</td><td>The framework does not contain pre-analysis elements for the decision-making process</td><td>Adopting framework aid in managing the essential elements of the supply chain operations appropriately</td></tr>
</table>

Table 13 Reflection results using SWOT analysis

5. CONCLUSION

In this chapter, we first conclude the results per the research question. This is followed by the limitations of this research. We conclude by presenting recommendations for future research as well as recommendations for practitioners.

5.1 SUMMARIZING THE RESEARCH QUESTIONS

RQ1 - What is found in the literature about the applications of AI/ML technologies in the fields of supply chain operations?

The AI/ML technologies have been highly applied in various sub-fields of the supply chain. For instance, demand and sales planning, inventory replenishment, production monitoring, inbound and outbound logistics, supply chain risk management, and integrated business planning. The findings determine that AI/ML technologies have been highly applied to improve the forecast accuracy in the supply chain operations, which helps make a correct decision and maximize the company's overall productivity. AI/ML technologies, on the other hand, have been used in the fields of production planning, inventory management, and logistics management as well. The applications of AI/ML technologies in production planning assist in handling the production monitoring operations and scheduling in a distributed manufacturing environment. It has also been adopted for effective inventory replenishment processes to ensure order fill rates and manage inventory costs efficiently. AI/ML technologies in businesses can help forecast demand surges and modify material flow routes and volumes. The use of AI/ML technologies in the supply chain aids in the development of a completely automated, self-adjusted decision-making system.

RQ2 - According to the literature, which problems in the supply chain operations have been addressed using AI/ML technologies?

In the supply chain operations and planning, we determined the problems related to inaccurate forecasting, unstable decision-making, operations planning, delaying selecting the suppliers, and lack of monitoring and managing. Due to the highly unpredictable nature of the market and the difficulties associated with demand planning, it is difficult to provide reliable forecasts. To address this obstacle, it is reported that the ANN technique is an appropriate AI/ML technology. On the other hand, the ANN technique has also been applied to avoid delaying selecting the suppliers during new product development. At the same time, fuzzy models and support vector AI/ML techniques have been reported to tackle inaccurate monitoring and production management issues. Overall, AI/ML technologies have been addressed to solve planning, sourcing, production, and delivery issues.

RQ3 - What metrics are reported to be helpful to assess the application of AI/ML in supply chain operations according to published literature?

To assess the application of AI/ML in supply chain operations, the established techniques, methodologies, and tools exist to identify the most critical supply chain performance measures and metrics. Which helps select KPIs and methods for analyzing and measuring the performance of the supply chain operations assisted by AI/ML technologies, which enable structured communication across a broad range of performance measurements, optimize the overall supply chain, and evaluate business operations. Analytical hierarchy process (AHP) and analytic network process (ANP) models were identified to select the critical KPIs and performance measurement and metrics of the supply chain operations and applications of AI/ML. At the same time, the data envelopment analysis (DEA) technique is used to identify inefficient processes and make the right decisions for the enhancement of business operations. The results indicate that there has been evolution and implementation of tools and techniques that would help to assess the application of AI/ML in supply chain operations.

RQ4 – According to the published literature, which capabilities are essential for implementing AI/ML technologies in supply chain operations?

For implementing AI/ML technologies in the supply chain operations, we determined the essential capabilities. Dynamic and agile capabilities reported helpful developing abilities to achieve strategic advantages in highly changing and dynamic environments. To strengthen the organization's resilience in highly unanticipated disturbances and interruptions to its supply chain operations, a resilience capability needs to be established as per findings. Whereas data management, analytical, and performance management capabilities are also critical capabilities, they assist supply chain organizations in efficiently managing data, implementing appropriate analytical technologies in supply chain fields, and tracking and monitoring the supply chain's overall performance.

RQ5 – How to design the framework that helps develop the capabilities for applying AI/ML technologies in supply chain operations?

Chapter 3 provides an answer for RQ5 and presents the proposed framework and a detailed description of its elements. The framework consists of three primary capability components, each of which has two sub-components. The first element of the framework is data management capability, and its sub-elements are data quality and data governance. The second element is analytical capability, and its sub-elements are business case development and AI/ML technologies implementation. The third element is performance management capability, and its sub-elements are the six sigma DMAIC method and KPIs dashboard development. The primary goal of data management capability is to improve supply chain maturity by maintaining data accuracy and increasing visibility and control throughout the supply chain in order to maximize agility and responsiveness. The sub-elements of the data management capability are data governance which plays a valuable role in defining processes, policies, standards, organization, and technologies required to manage and ensure the availability, accessibility, quality, consistency, and security of data in an organization. Whereas, the data quality plays an essential role in improving the quality of the high volume, variety, velocity, veracity of raw data by applying noise filters to remove the bad quality of data and sub-processes for integration and filtering data for transformation/normalization.

On the other hand, analytical capability plays an essential role in proposing suitable AI/ML technologies in the supply chain fields like planning, sourcing, production, and delivering. It also helps to automate, augment and enhance customer experience and decision-making process. The sub-elements of analytical capabilities are business case development, which allows organizations to calculate the costs, benefits, and risks that will mitigate significant project failure and negatively impact the organizations. At the same time, AI/ML technology implementation plays a vital role in adopting predictive analytical techniques like AI/ML in supply chain operations. Which would help drive the supply efficiently under uncertain conditions.

The performance management capability helps to analyze, monitor, and improve their existing supply chain management processes to beat market competition and stay competitive. In this regard, the sub-elements proposed are the six sigma DMAIC methodology and KPIs dashboard. Adopting the six sigma DMAIC method enables the organization to review their existing supply chain management practices and guide them in making improvements. It focuses on reducing variation, measuring defects, and improving the quality of products, processes, and services. Whereas developing KPIs dashboard with essential features help in measuring and monitoring supply chain performance, which can reveal the gap between planning and execution and helps companies identify potential problems and areas for improvement. It enables organizations to determine and explain how the organizations are progressing to meet the business objectives.

RQ6 – Is the framework finds useful and relevant by the practitioners?

Chapter 4 provides an answer to the RQ6 and provides detailed descriptions of the proposed framework evaluation process and evaluation outcomes. To evaluate the proposed artifact, three semi-structured interviews were conducted. The semi-structured interviews were performed following the approach described in (Boyce. & Neale, 2006) for conducting in-depth interviews. The evaluation outcome aimed to determine the usefulness, feasibility, and impact of the supply chain capability framework when adopted in the organization. The results from the evaluation determine that the overall strategy and elements of the framework will be useful and found to be essential pillars in addressing the critical issues that companies face. Adoption of the framework would be feasible but depending on the organization's structure and goals. Whereas implementing the framework in organizations can have considerable benefits of improves productivity and customer satisfaction.

5.2 LIMITATIONS

Despite the fact that the study has addressed the main research question and associated research objectives, it has some limitations. The supply chain capability development framework is designed only to focus on capabilities required for adopting advanced innovative analytical technologies in the supply chain organization. This choice was made to keep the scope of this study manageable. But on the other hand, the framework can also be adopted for managing supply chain operations by implementing basic analytical techniques in the organizations. In this case, the organizations need to put more effort into adopting organizational changes and heavy financial investments, which results in adding little value to the organizations.

The framework has focused only on data management, analytical, and performance management capabilities for adopting advanced analytical technologies in supply chain organizations. This is a limitation in developing an organization's ability to plan, design, and implement all types of change efficiently with committed stakeholders, causing minimal negative impacts on people and operations to consistently achieve the desired business and cultural results after adopting the framework. Adding a change management capability element to the framework might overcome these limitations.

Due to the fact that the interviews are performed with a small number (three) of interviewees. As a result, this qualitative analysis is confined to the interviewees' knowledge, experiences, and perspectives. Conducting the same interviews with a larger sample size may produce different or additional results. The limitation with respect to the interview-based evaluation is that the framework is evaluated using a graphical representation of the framework and some additional explanation. This might affect the interviewees' view of the framework since there is more to the framework (the detailed textual recommendations) than the graphical representation.

Finally, the framework is created based on academic literature, although it is aimed at helping practitioners. There might be a difference between the topics academic literature addresses and what practitioners experience in practice. However, it must be noted that the framework was created based on academic theory instead of practical experiences by supply chain consultants and from real-world analytical supply chain projects. As a result, there may be an inherent misalignment between the framework and practice.

5.3 RECOMMENDATIONS FOR FUTURE RESEARCH

For future research, we recommend evaluating the framework with a larger group of practitioners. This will result in more varied insights into the quality of the framework. This way, the framework's gaps, and flaws can be more thoroughly identified and improved. Additionally, the framework could be evaluated by practically adopting it within the supply chain organization to determine its usefulness and impact on the operations.

Based on the evaluation through interviews, the change management capability component needs to be added to the framework to determine what abilities are required to be developed to handle smooth managing and understanding needs and the impact of the changes, to identify how to align resources within the business to support the change. Additionally, which sub-elements need to be added to support the change management capability element. This would help to identify the effectiveness of the framework in the supply chain organization.

Another recommendation for future work is related to the framework, which is based on extensive scientific literature research. Therefore, there might be a mismatch, or bias, due to the academic theoretical basis. It would be interesting to develop a similar framework from a practical perspective. This might result in different perspectives on the framework and might contribute to improving the framework for practical implementation in supply chain projects.

5.4 RECOMMENDATIONS FOR PRACTITIONERS

The designed framework can become a significant starting point for developing the capabilities for adopting innovative analytical technologies in supply chain organizations. As it includes all basic essential elements for data management, adopting analytical techniques, and managing the supply chain performance.

For practical implementation of the framework and developing data governance strategies in the organization. We recommend practitioners hire external data governance consultants who can help identify and prioritize data assets and develop standardized data management planning, oversight, and control procedures and policies efficiently. For improving the quality of the data, we recommend practitioners identify the source of data and find effective techniques and IT infrastructure solutions in processing and storing the data securely.

Additionally, we recommend practitioners make collaboration plans with the key stakeholders from different teams to plan and make decisions integrated regarding the adoption of the framework, which helps in continually achieving focus, alignment, and synchronization among all organization functions.

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APPENDIX 1

Framework for developing a business case by (Ward et al., 2007)

	Doing New Things	**Doing Things Better**	**Stop Doing Things**
Financial	Benefit – Measure – Benefit Owner –	Benefit – Measure – Benefit Owner –	Benefit – Measure – Benefit Owner –
Quantifiable	Benefit – Measure – Benefit Owner –	Benefit – Measure – Benefit Owner –	Benefit – Measure – Benefit Owner –
Measurable	Benefit – Measure – Benefit Owner –	Benefit – Measure – Benefit Owner –	Benefit – Measure – Benefit Owner –
Observable	Benefit – Measure – Benefit Owner –	Benefit – Measure – Benefit Owner –	Benefit – Measure – Benefit Owner –

APPENDIX 2

Artifact Evaluation Questions

6/30/2021 Artifact Evaluation Questions

Artifact Evaluation Questions

1. 1. Do you find the framework is useful and relevant for supply chain organizations?

2. 2. Is it feasible to adopt the framework in organizations?

3. 3. In your view, do organizations need to fulfill any additional requirements before adopting the framework?

4. 4. Does the sequencing appear logical when adopting the framework in an organization?

5. 5. Based on your experience and perceptions, how much impact would the framework have if one implements it in the organizations?

6. 6. Are there, in your view, any suboptimal aspects? Aspects that need improvement? For example, incomplete aspects?

APPENDIX 3

Artifact Evaluation slides

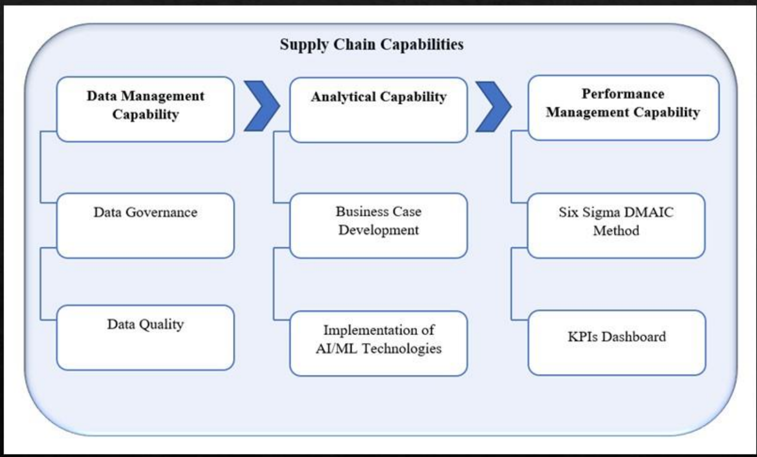
Thesis Topic

- Design a framework to develop capabilities for adopting AI/ML technologies in the supply chain.

Research Questions and Objectives

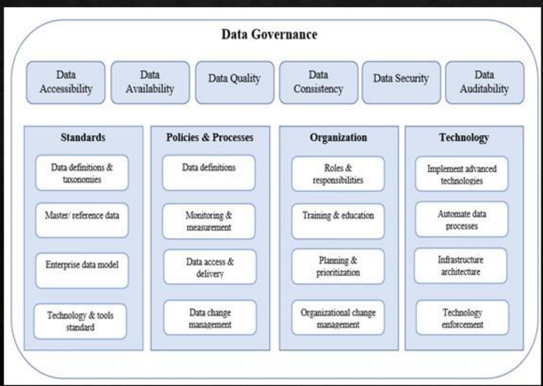
- How to develop the capabilities for effective applications of AI/ML technologies in supply chain operations?
- Conduct a literature review regarding applications of AI/ML technologies in supply chain operations.
- Decide on what information will be used for this research to design the artifact.
- Describe the proposed framework.
- Evaluate the proposed framework.
- Discuss the limitation, further research, recommendations, and the results.

Supply Chain Capability Development Framework

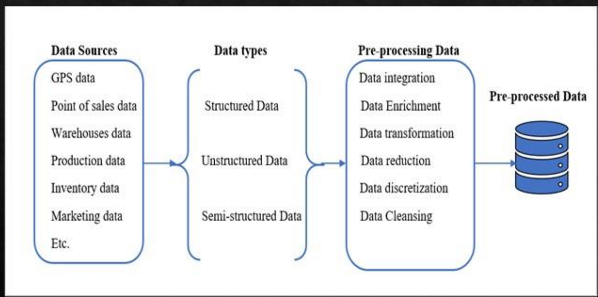


Data Management Capability

- Data Governance



- Data Quality



Analytical Capability

- Business Case Development for adopting AI/ML technologies, as per framework proposed by Ward et al., 2007.
- Implement suitable AI/ML techniques in the supply chain fields.

Performance Management Capability

- Iimplement Six Sigma DMAIC methodology.
- Develop supply chain KPIs Dashboard with key features and functionalities.