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A Systematic Review of Blockchain in Supply Chain Management

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ABSTRACT

In today's international supply chain economy, demand fluctuation is disruptive and expensive. Traditional supply chain management systems include high complexity, centralized organizational structures, poor system design, increasing expenses, and a requirement for speed, quality, and service. Finance and security are crucial in centralized supply chain management since the revenue head bears the full operating expenses, from collecting materials to distributing finishing goods. Customer behavior varies; therefore, income may not match spending everywhere. Traditional supply chain management relies on small committee for speed, cost, and security. So, this dynamic consumer behavior requires a safe, decentralized, and trustworthy ecosystem. Decentralization increases supply chain financial decision making. Blockchain the fastest-growing technology, solves today's supply chain problems. Blockchain allows huge network of decentralized independent people and organizations to flourish and run smoothly in a distributed operating environment. If the writer is trustworthy its data cannot be changed or faked. Blockchain has pros and cons: decentralized network in centralized computers. Blockchain issues include altering web page data to malicious data, network synchronization, service interruption, and more. Food, textile, healthcare, and educational institutions may use the suggested supply chain management approach. The supply chain management system is simulated in multiple scenarios for root-cause analysis of threats, vulnerabilities, and dangers. A thorough explanation of on why attacks happen, how to avoid them and how to protect the secure supply chain management from numerous threats and weaknesses.

KEYWORDS
Blockchain,
Decentralization,
Supply Chain,
Consumer Behavior,
Financial Decision Making

1. INTRODUCTION

Improvements in cost saving, customer service, dependability, and speed of delivery are just some of many ways in which information system (IS) have become standard fare in the manufacturing, operations, and supply departments of today's successful businesses. Information systems are used by business at the strategic, tactical, and operational levels of decision making to gather, store and analyze information [1]. Business may improve their worth, efficiency, competitiveness, and effectiveness by using information systems [2]. Decision analytics is the act of gathering information from different business processes utilizing IS and analyzing it to get insights for decision making [3]. An essential component of information systems, decision analytics plays a crucial role in guiding stakeholders towards the best possible outcomes [4]. In this work, we used IS for deliberation by combining it with other research techniques. Studies of process, people, and technology (PPT) in an organizational setting may be found in the IS literature. Beginning in the 1960s, when American management psychologist Dr. Harold Leavitt presented a four-part company management model consisting of "task," "structure," "people," and "technology," the seeds of what would become known as "project portfolio management" were being planted. Later, these four factors were reorganized as PPT (task and structure were rethought as process), and it is still widely recognized as a powerful framework for managing a business. Many procedures are used by employees to get work done in a company, and technology helps make these processes more effective [5]-[10]. This research aims to increase the overall operational efficiency of the container supply chain by capitalizing on the significance of this framework within a supply chain environment.

Information and communication technology (ICT) have contributed to the rise in popularity of supply chain management (SCM) (Alfalla-Luque & Medina- López, 2009). The purpose of this research is to apply IS (International Standards) for decision analytics to the field of supply chain management [11]-[15]. The research focuses on one specific sector: The Container Supply Chain (CSC) sector. Many entities such as port terminals, ocean forwarders, freight forwarders, maritime liners, etc. are involved in the CSC, making it one of the world's most vital supply chains [16]-[20].

1.1 Background of Container Supply Chain

Freight transportation (logistics management of commodities between multiple nodes) was a vital feature of the industrial revolutions of the early 20th century, and it grew much more essential when international trade and commerce expanded in the late 20th century [21]. Shipping commodities across international borders in the 1940s required a lot of people and time due to the complexity of multimodal transportation, which employed many modes of transport to get items from one region to another [22].

As Malcolm McLean came to this conclusion, he saw that the lack of uniformity was the true problem [23]. McLean influenced the development of the shipping industry in the

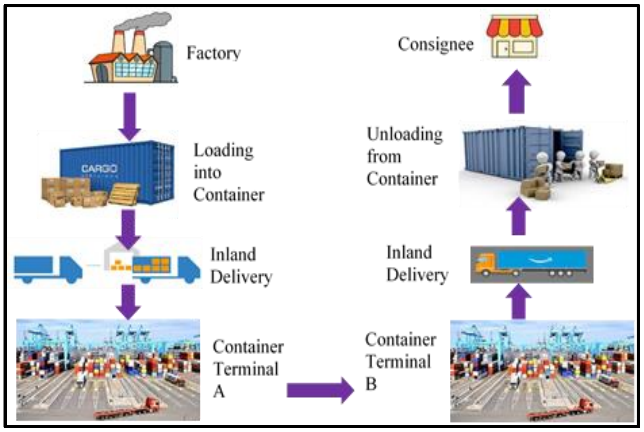

Fig. 1 Different stakeholder in container supply chain

middle of the 20th century by standardizing the trailers or containers used in business today. Containers are now an integral part of the international supply chain because of standardization. In 2016, Levinson discussed the many effects of containerization on the international economy [24]-[30]. Shipping containers and their associated logistical systems have become an integral part of the global economy. Several different groups and individuals have a stake in CSC. Fig. 1 depicts and describes the major players in CSC

Port Terminal

A port terminal is a facility used for the loading, unloading, shipping, and transferring of cargo containers between various modes of transportation. General cargo, bulk freight, and passenger traffic are handled by six distinct kinds of port terminals [31]-[35]. Three different types of terminals—the break-bulk terminal, the neo-bulk terminal, and the container terminal—handle the general cargo that is transported. Port terminals that specialize in bulk cargo are known as 4) liquid bulk terminals and 5) dry bulk terminals. The 6) ferry and cruise terminal is responsible for passenger services. Modern port terminals include ferry and cruise terminals, however there aren't many of either [36].

An integral part of any CSC is the port terminal. Keep in mind that a port is not the same thing as a port terminal. A larger port may include many terminals, each specializing in a distinct kind of cargo that may be processed all at once [37]. While the government owns most ports, some are privately held, such as the Adani Group's Mundra port in Gujarat.

Dry Port

The Dry Port (DP), also known as an Inland Port, is a transshipment site from which goods coming from the Sea Port are sent to other locations around the country. Both a road network and a rail network link the DP directly to the port terminal at the sea [38]-[41]. Cargo transportation efficiency, operations, and sorting efforts are all enhanced. It also facilitates a wide range of operations that were previously limited to the port terminal. The whole container supply chain benefits from the shortened dwell time [42]. For a well-oiled container supply chain, DP's central position is vital. DP was strategically placed to provide rapid transportation without compromising on accessibility. Rail connections should be able to provide as a backup for when roads to interior locations are unreliable.

1.2 Blockchain technology in container supply chain

Distributed ledger technology like blockchain (BC) might dramatically alter the logistics industry. Immutability (Du et al., 2019), a consensus process (Nakamoto, 2008), and auditability are some of BC's most notable practical features (Strainer et al., 2021). As it can withhold any transactions and ensure data transparency, dependability, traceability, and authenticity (Galeazzi et al., 2019; Kamble, Gunasekaran, & Sharma 2020), it finds its application in such settings (Sikorski et al., 2017). As a result of these qualities, BC is gaining traction in a variety of industries, including agriculture (Kamble et al., 2020; Saberi et al., 2019; Sikorski et al., 2017), finance (Du et al., 2019), and healthcare (Sikorski et al., 2017). (Kshetri, 2018; Saberi et al., 2019). But progress and widespread use of the technology are in their infancy (Saberi et al., 2019). Although there is a growing body of research on the use of BC in the food and agricultural industries (Kamble et al., 2020; Kshetri, 2018; Saberi et al., 2019; Sikorski et al., 2017; Stranieri et al., 2021), there is a dearth of research on its usage in other critical industries.

The use of blockchain technology in the field of CSC (Container Supply Chain) is quite broad. IBM, a market leader in computer software, partnered with Maersk, a global shipping giant, to use blockchain technology for CSC (Container Supply Chain) in January of 2018. Maersk's cargo from East Africa to Europe was analyzed, and it was determined that the package had to go through 30 different agencies and include 200 separate contacts between those authorities (Groenfeldt, 2017). As a result, in September of 2016, IBM and Maersk ran a proof of concept (POC) for blockchain on a shipment going from Mombasa, Kenya, to Rotterdam, the Netherlands. The POC was successful in that it was able to save shipping costs by 15%. (Groenfeldt, 2017). As a result, a vast new frontier for blockchain in CSC opened. Table 1 details some of the ways in which blockchain technology might be used to improve CSC procedures.

Table 1 Literature related to container supply chain employing blockchain.

Focus area	Reference
Less Container Load (LCL) optimization	(Tan et al., 2018)
Smart shipping	(Komathy, 2018)
Traceability	(Asioli, D., Boecker, A., & Canavari, M. (2014))
Blockchain prototype	(Zhang, et. al., 2022).)
Theoretical framework	(Gausdal et al., 2018)

The inefficiency of the whole supply chain is amplified by the excessive paperwork required for CSCL (Certified Supply Chain Leader) operations. The delay in paperwork causes the cargo ships to be out of sync by several days [43]-[46]. To keep everything running smoothly, the port authorities, the ocean carriers, and the inland carriers (trucks) must all be in sync with one another. Just-in-time services rely heavily on this kind of synchronization. Due to the large number of people that need to communicate throughout CSCL, the process is slowed down unnecessarily.

The first and foremost guideline of supply chain management is to minimize the number of touchpoints (between procedures and parties involved) [47]-[50]. By establishing mechanisms for real-time information exchange, traceability, and transparency among the many stakeholders in the CSCL, we can decrease the number of unnecessary encounters between them. They'll be able to optimize their procedures in advance, which will benefit the whole supply chain. In addition, sustainability may be attained by the efficient and effective management of available resources. Thus, sustainable supply chain operations are also the result of collaborative information exchange amongst many stakeholders [51]-[55].

The study's overarching goal is to use ICT to investigate two specific research questions.

RQ1: How can we better predict the flow of containers at CSC?

RQ2: What are some ways in which CSC might make advantage of the blockchain's action potential to boost the effectiveness of its operations?

The following two study goals are created to address the questions:

1) One goal is to create a univariate, multivariate model for predicting container throughput using deep learning.
2) Recognize the practical applications of blockchain technology in container logistics and supply chain.

The paper is structured as follows: Section 2 covers the context and literature review, Section 3 details the recommended approach, and Section 4 wraps things up and looks forward.

2. LITERATURE SURVEY

At outset, to understand the current advances in the field of information systems for supply chain management, the text mining of the literature is carried out with the search keywords like "information systems", "information technology", "communication technology", in the first level of search and keywords like "supply chain management", "supply chain", "operations management", "operations research", in the second level of research. As a result, several research themes emerged which were common for information systems and supply chain management. For the selection of research area for the proposed work, the word cloud of the top forty research themes was developed for better visualization, as shown in Fig 2. Despite many publications in supply chain management and information systems in solidarity, very limited literature is available on the intersection of two disciplines in recent years. Since our application area is CSC, we investigated the thematic and temporal evolution of research in CSC. Digital technologies are observed to have provided valuable business opportunities in container logistics (Buratti, N., Parola, F., & Satta, G. (2018). The contemporary literature on container supply chain is observed to have registered digital transformation (Tijan et al., 2021, Gunes et al., 2021), digital infrastructural advancement (Canepa et, 2021), information communication technology for improved coordination (Gonzalez et al., 2021) and efficient information exchange (Buratti, N., Parola, F., & Satta, G. (2018) among different stakeholders in container supply chain using information systems. The brief introduction to contemporary information systems-based studies in CSC is shown in Table 2

Table 2: Contemporary topics of study in information systems for container supply chain

Area of study	Reference
Digital transformation	(Canepa et al., 2021)
Port digitization	(Brunila et al., 2021) (Pu & Lam, 2021b) (Gonzalez et al., 2021)
ICT	(Gonzalez et al., 2021) (Buratti, N., Parola, F., & Satta, G. (2018)
Blockchain	(Zhang et al., 2022) (Pu & Lam, 2021b)
Social media analytics	(Dominguez et al., 2021)
Artificial intelligence	(Lyridis, 2021) (Khashei, M., & Bijari, M. (2010) , (Liu et al., 2020)
Deep learning	(Kong et al., 2022), (Punia et.al., 2020a)
Authentication and Security	(Zhang et al., 2021) (Wang et al., 2022) (Liu et al., 2020)
Prediction	(Alizadeh et al., 2021) (Liu et al., 2020) (Tang et al., 2020) (Xiao et al., 2020)
Emissions	(Yuan et al., 2020) (Yu, Fang, et al., 2021) (Cammin et al., 2020)
Sustainability	(Wang et al., 2020) (Yu, Fang, et al., 2021) (Yuan et al., 2020) (Bai et al., 2021)
Anomaly detection	(Hu et al., 2022) (Balci & Surucu-Balci, 2021)
Internet-of-Things (IoT)	(Hu et al., 2022) (Gonzalez et al., 2021) (Buratti, N., Parola, F., & Satta, G. (2018) (Balci & Surucu-Balci, 2021)

Thematic examination of the CSC literature reveals eight distinct themes or aspects. Each fundamental topic is broken down into its component parts. Intermodal transport, shipping network design, data analytics, operational planning and management, ship routing and scheduling, container supply chain optimization, bunkering and tank allocation, sustainability, and other related topics have been recognized as key areas of focus. CSC research has paid more attention to the second sector of transportation, which includes not only cars but also aircraft and trains. When concerns about policy give way to those about national security, transoceanic transit gives way to intramodal transportation. Several new research avenues into CSC have emerged in the last several decades. There may have been minor vocabulary changes from one division to another, but the basics remained the same. The term "optimization" is renamed "computational technique" or "algorithm" in the second group, "optimization" returns in the third, and "multi-objective optimization" is introduced in the fourth and final group. All the key ideas are expected to be present in scholarly works on CSC. Still, there have always been changes in industrial policy, regulation, national security, accident prevention, digitization, etc. Emerging technologies including forecasting, information analysis, blockchain, artificial intelligence, etc., have been the focus of much recent research, and this is reflected in the results of advancements in IS literature pertaining to operations management. As a result, the planned work is organized around examples of process, technology, and people as the three pillars upon which IS rests. Within the CSC, the concentration is on "Forecasting," is the most crucial aspects of SCM. "Blockchain Technology" will be the center of technical interest at the CSC. As a last People-related matter, the investigation of the "social media" use patterns of different CSC stakeholders (container logistics enterprises and maritime lines) is carried out. In what follows, we conduct a comprehensive literature review of the aforementioned areas of study, identify research gaps, and propose future lines of inquiry and objectives.

2.1 A Literature Analysis on Supply Chain Prediction Using Containers

When comparing the financial sector with the container supply chain and logistics sector, the financial sector is where machine learning is being examined at a much greater depth (Liu et al., 2021). Today's CSC research, however, is following a new course as machine learning finds its way into the container transportation sector in pursuit of greater operational efficiency (Shankar et al., 2021). It is already challenging to anticipate or analyze marine data because of its inherent volatility (Liu et al 2021). Recent studies on CSC have shown unsatisfactory foresight on a range of activities at the strategic, tactical, and operational levels (Xie, et.al. 2019). It has been shown that machine learning methods are effective in resolving supply chain issues and producing more accurate forecasts (Nguyen et al., 2018). For many organizations, the choice to make a demand prediction is a crucial engine in the supply chain and logistics system (Punia et.al 2020a). The ability to predict demand with high precision allows for more efficient use of resources and more sound judgement. Considering the magnitude of the container logistics market, even a little efficiency gain may have a significant impact on bottom line results (Shankar et al., 2021). This is why improved demand forecasting models are a constant goal for the industry. To this end, a comprehensive analysis of the existing literature on CSC container throughput forecasting models is conducted. To grasp the usefulness of various forecasting techniques, it is crucial to get familiar with their defining features. Predictive model selection is challenging due to the wide variety of data types. It is econometric models or machine learning models that do the forecasting in the existing literature. Predicting and estimating the necessary variable or determining the impact of the explanatory economic variable are among the goals of the econometric models that use statistical methods for this purpose. One of the most common types of economic models is the regression model. Time series forecasting using autoregressive (AR) and moving average (MA) processes was created by Box and Jenkins, and it is most effective with linear time series. Further research, however, showed that most time series are nonlinear, and hence the Box and Jenkins approach was not an effective way to capture the dynamics of time series (Akkermans et al, 2004). As a result, ANN has shown a great deal of promise in explaining the nonlinearity of time series (Alizadeh et al, 2011). To take use of ANN's strength in capturing nonlinearity effectively, several variants have been created, such as ANN with exogenous input (Kummong and Supratid, 2016) and quasiperiodic ANN for predicting the average return on industrial investments (Bodyanskiy and Popov, 2006). It has also been found that adaptive ANN (Wong et al, 2010) and the hybrid adaptive neuro-fuzzy inference system (ANFIS) outperform traditional ANN (Alizadeh et al, 2011). ARIMA + ANN is seen as extremely promising in the current research on container throughput predictions (Tseng, Yu, and Tzeng, 2002; Wang and Jiang, 2019; Xiao, Xiao, and Wang, 2012; Zhang, 2003).

Throughout the years, researchers have become better at predicting container throughput by using more complex approaches and procedures. You may divide the models used to predict container throughput into two major categories: univariate and multivariate. Univariate and multivariate models might be based on econometric forecasting techniques, machine learning, or a hybrid of the two. Hybrid models, which use both econometric and machine learning-based techniques, may effectively account for both non-linearity and temporal dependence. The univariate and multivariate container throughput forecasting models are described in depth in this section.

2.2 A Retrospective on Single-Variable Predictions of Container Throughput

Logit models (Veldman & Bäckmann, 2003), error correction models (Fung, 2002), vector error correction models (VECM) (Fung, 2001), and a formula derived from diversion distance and transshipment volume were all used to predict container throughput prior to 2003. (Zohil and Prijon, 1999). Later, people started using techniques like moving averages and decomposition models (Schulzea and Prinzb, 2009). Using an autoregressive distributed-lag model, we calculate the container throughput elasticity between the ports of Hamburg and Le Havre (van Dorsser, et. al. 2011). The spatial-temporal study of China's Ningbo- Zhoushan port is performed, and the ARIMA model is used to provide a 2026 prediction for container throughput (Feng et al, 2019). The approaches for predicting time series are presented by Chan, Xu, and Qi in a portfolio format (2018). Gao, Luo, and Zou (2016) evaluate and contrast many alternative model selections and model averaging strategies and find that the latter provide superior results. Seasonal ARIMA (SARIMA) and Holt-exponential Winter's smoothing (ES) are both averaging methods that lead to very similar outcomes (Ee et al, 2014). SARIMA outperformed Holt-ES, Winter's however, while attempting to forecast German transshipment container traffic (Schulzea and Prinzb, 2009). Nonetheless, Winter's approach was shown to be more precise by Diaz et al. (2011). This article compares the seasonal ARIMA model to Holt- technique. Winter's Single and hybrid model projections often use the SARIMA model, however Chen and Chen found that GP models outperform SARIMA by 32%-36%. Discrete particle swarm optimization is only one example of a meta- heuristic applied to predict port container throughput (Xiao et al, 2014). The ARIMA model is often used in univariate time series forecasting (Makridakis and Hibon, 2000). The meta-heuristics are left out of our analysis since we are only interested in the most recent developments in sequential-learning-based time series models. To provide a more precise prediction of container throughput, several econometric and machine learning techniques are hybridized. By using an ARIMA model to predict the low-frequency components of the series and a support vector regression (SVR) model to predict the high-frequency components, a hybrid decomposition ensemble is discovered increase forecasting accuracy and stability (Niu, Hu Sun, and Liu, 2018; Mo et al, 2018). In a similar vein, SARIMA, and least square support vector regression (LSSVR) are used (Xie et al, 2013), however ARIMA and ANN are the most often utilized because to their superior prediction accuracy (Tseng et al, 2002; Wang and Jiang, 2019; Xiao et al, 2012; Zhang, 2003). Most often, hybrid models are presented so that both linear and nonlinear aspects of time series may be accommodated. Gang Xie, Zhang, and Wang's (2017) hybrid model incorporates decomposition ensemble and data characteristic analysis (DCA). As the nonlinear component in the container data must be considered, Xie, Qian, and Yang (2019) employed the DCA in their hybrid technique [56]. The Markov chain model and grey system are employed with traditional time series approaches to foretell the possibility of rising and falling container traffic patterns from year to year. Gray modelling considers initial data buildup because of a linear dynamic process; nonetheless, it is only applicable to short-term forecasting (Liu and Forrest, 2010).

It has been argued that it is impossible to determine with certainty which forecasting model should be used with which (Makridakis et al, 1982; Peng and Chu, 2009).

But Peng and Chu (2009) found SARIMA and classical decomposition approaches to be better for predicting univariate container throughput. Here, the most popular SARIMA model is employed with decomposition techniques like Winter's and Holt- Winter's The field of container throughput forecasting also has 51 a lot of untapped potential when it comes to state-of-the-art time-series algorithms like ETS and TBATS [57]. Time series approaches have come a long way, but their potential use in CSC remains uncharted.

2.3 A Look at Several Models for Predicting Container Throughput

Initial research on multivariate CT forecasting is often done on a regional scale. Zohil & Prijon (1999) establish a method for predicting CT in the Hamburg-Le Havre corridor using data on transshipment volumes and diversion distance. Another Hamburg-Le investigation uses a linear regression model to examine the connection between container throughput and GDP (Verbeke et al., 1996). In addition, the Hamburg-Le port's future is projected for the next century using the causal model, using GDP as the driving factor (van Dorsser et al., 2011). Three-stage methodology using an autoregressive distributed lag model and economic scenarios captures the possible effect of individual risks at this port (Rashed et al., 2018). As a result, it is easier to make choices involving investments, and a connection may be made between CT and economic issues. Table 3 provides a summary of the univariate forecasting model.

Distributed ledger technology can withhold any transactions and ensuring data transparency, dependability, traceability, and authenticity (Galeazzi et al., 2019; Kamble, Gunasekaran, & Sharma 2020), it finds its application in such settings (Sikorski et al., 2017). As a result of these qualities, BC has been gaining appeal in several industries, agriculture (S. S. Kamble et al., 2020; Saberi et al., 2019; Sikorski et al., 2017), finance (Du et al., 2019), and healthcare (Kshetri, 2018; Saberi et al., 2019). But progress and widespread use of the technology are in their infancy (Saberi i et al., 2019). Yet, although there there is is a a growing body of research on the use of BC in the food and agricultural industries (S. S. Kamble et al., 2020; Kshetri, 2018; Saberi et al., 2019; Sikorski et al., 2017; Stranieri et al., 2021), there is a dearth of research on its usage in other, equally vital fields. From its inception, BC technology has been seen as a potentially game-changing digital disruption (Kshetri, 2018). Several fields have discovered uses for it. If we take the food and agricultural industries as an example (S. S. Kamble et al., 2020; Saberi et al., 2019; korski et al., 2017), BC is used to guarantee traceability (Creydt & Fischer, 2019) and food safety (Kamath, 2018).

Table 3: Models used for univariate container throughput forecasting

Forecasting Method used	References
ARIMA/SARIMA	(Feng et al., 2019), (Farhan & Ong, 2018) (Pang & Gebka, 2017) (Ee et al., 2014) (Shu et al., 2014) (Xie et al., 2013) (Xiao et al., 2012) (Kou et.al 2011) (S.-H. Chen & Chen, 2010) (Schulzea & Prinzb, 2009)
Decomposition-ensemble	(Xie et al., 2019)(Niu et al., 2018) Xie et al., 2017) (S.-H. Chen & Chen, 2010)
Regression model	(Rashed, Meersman, Sys, Van de Voorde, & Vanelslander, so) (Gamassa & Chen, 2017) (Gosasang et al., 2011) (Veldman & Báckmann, 2003)
Neural network	(Mo et al., 2018) (Xiao et al., 2012) (Gosasang et al., 2011)
Non-time series methods	(Huang et al., 2014) (S.-H. Chen & Chen, 2010)(Huang et al., 2016)
Portfolio of forecasting methods	(H. K. Chan et al., 2018) (Peng & Chu, 2009)

Big box stores like Walmart used BC to boost the safety of their Mexican mango stock (Kamath, 2018). Coca-Cola has adopted BC to prevent using indentured labour (Chavez-Dreyfuss & Reuters, 2018). In a similar vein, the PDO/PGI products' use of BC for authentication and food quality assurance was studied (Scuderi et al., 2019). Beyond this, it was suggested that BC be used in the logistics industry to handle product ownership claims and overcome the difficulty of identification (Toyoda et al., 2017). The Maersk-IBM partnership recently disclosed one of the most talked about uses of BC in the logistics industry (Groenfeldt, 2017). Cost savings might be substantial, they claim. Bill of Lading (BOL) (Bill of Lading) management utilizing BC to ensure accuracy and reliability in container logistics. Nevertheless, information on the implementation of

BC in container logistics is scarce in academic literature. The effects of BC on supply networks have been the subject of several studies. To make the supply chain more trustworthy, safe, transparent, and genuine, it is essential that the problems of product visibility and transparency be resolved (Galeazzi et al., 2019). To better manage data and ensure that products adhere to international standards, Galeazzi et al. 2019 suggested a BC-based ecosystem. In addition, it explains why business process modelling (BC) is necessary for effective supply chain management and how to implement it. Transparency, responsiveness, efficiency, food quality, and adaptability are some of the performance parameters used by (Stranieri et al., 2021) to investigate the impact of BC on the agri-food supply chain. The findings revealed how BC affected financial outcomes like ROL. In addition, it highlights the beneficial effects of BC on information management via the promotion of information exchange, accessibility, and transparency (Stranieri et al., 2021). There are few examples of BC adoption in the literature and most of those that do exist have focused on metrics (Stranieri et al., 2021). The research suggests that to improv the implementation of BC, sector-specific studies on BC adoption are needed (S. Kamble et al., 2019). The effects of implementing BC in supply chains have been widely discussed in academic literature. Many of these works are exploratory in character, while others are more narrowly focused on technical details. There is a dearth of information on the use of BC throughout the supply chain, and much less on its use in the container shipping industry. The potential for BC to be transparent and real has been well-documented, but the issue of how BC adoption would meet corporate needs has received far less attention.

3. PROPOSED METHODOLOGY

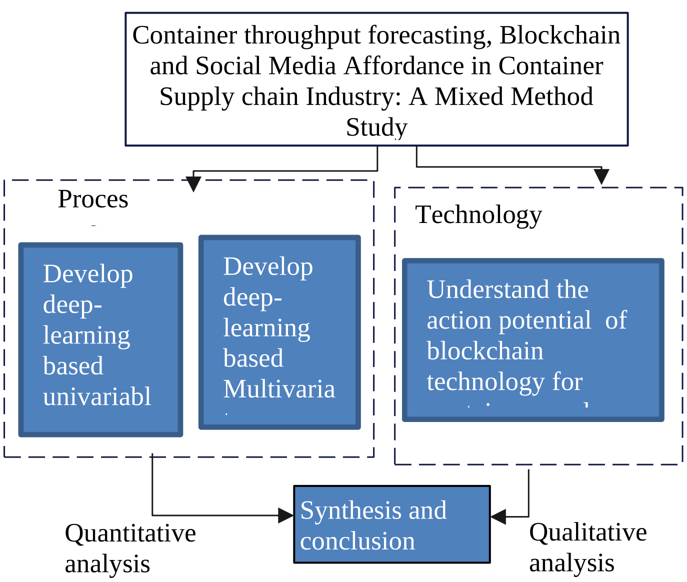

Fig 2: Framework of the proposed work

Data systems influence SCM processes like product and service planning, procurement, and distribution (Daneshvar Kakhki & Gargeya, 2019). There has been a connection between IS and SCM ever since the 1960s, when the concept of electronic data interchange (EDI) was created to store and process data (Daneshvar Kakhki & Gargeya, 2019). As a result of EDI, lead times and procurement mistakes were cut, boosting the efficiency of SCM activities. The effectiveness of the supply chain operations has been enhanced by several subsequent IS-based tools and methods, such as material requirement planning, manufacturing resource planning, enterprise resource planning, etc. Because of the increasing complexity of today's supply networks, many companies are adopting digital supply chain management systems (Alfalla-Luque & Medina-López, 2009). During the last decade, scientists have worked to perfect IS-based decision analytics systems for supply chain management (Daneshvar Kakhki & Gargeya, 2019). In this vein, we have developed an IS-based decision support system for the container supply chain as part of our study (CSC) [58].

The suggested research is one of the few studies that allows for both qualitative and quantitative methods. The whole proposed work, as seen in Figure 2, is generally separated into qualitative and quantitative research to encompass all three parts of IS: process, people, and technology. In the context of CSC, quantitative research is used to examine both processes and individuals. Yet, in the context of CSC, technological research is done using a qualitative research paradigm. The conceptual framework for the study is laid forth in this introduction proposed work, and the significance of the study's topic is emphasized. In this proposed work, we also talk about how broad or narrow the research is. The CSC is a cornerstone of international cooperation. Trade, or the importing and exporting of products, has increased because of globalization, which has reduced the distance between countries. Commodity demand rises in tandem with national GDP. The increase in demand is met thanks to international commerce. Seventy percent of global commerce in terms of value is transported by marine transportation, and more than half of it is transported by the container shipping industry, so it's easy to see why the container supply chain is so crucial. From 2007 to 2016, the top twenty ports in the world had an average rise in container traffic of 13.7 percent. This is according to the International Association of Ports and Harbors (IAPH). As a result of this dramatic growth, there is a need to explore new ways of managing container logistics to ensure that shipping continues as usual. Consistent with the sustainable development targets set by the United Nations [59]. To save money on transportation costs, most international commerce is conducted through ship, which can carry hundreds of tons of goods at once. Being the backbone of the freight transportation sector, container logistics necessitates an awareness of shipping industry and marine transportation history and development. Finding ways to enhance current practices and address problems currently facing the sector is crucial. Given that CSCL controls a value chain worth billions of dollars, even a modest improvement in operations and supply chain would have far-reaching consequences for the company and economies throughout the globe. So, the purpose of this proposed work is to investigate IS components (process, technology, and people) as they relate to CSC. The forecasting process is selected for analysis because of its relevance to business. The ability to accurately predict future events is crucial to many aspects of running a company (Hogarth & Makridakis, 1981).

While making important supply chain decisions like forecasting, it's important to use various layers of predictive analytics approaches and processes (Ee, J. Y. C., Kader, et.al. 2014). With the advent of machine learning (deep learning) based predictive analytics, these methodologies and processes are continuously improving. Indirectly or directly, the efficiency of many business processes improves because of improved forecasting since better forecasting leads to better management and planning of the operations. Consequently, the purpose of this research is to investigate how to optimize the predictive power of machine learning (deep learning) [60]. The widespread use of blockchain technology has the potential to revolutionize current business practices. As this is a relatively recent technological advancement, there is not much written about its possible applications. So, the purpose of this proposed work is to use qualitative methods to investigate the possibilities for action presented by blockchain technology in the context of CSC. The Covington virus epidemic severely impacted all our daily lives throughout the time of our research [61]. Almost all of humanity was quarantined. The proposed work's original goal was to conduct an in-depth analysis of the companies and individuals involved in the container logistics business; however, we refocused our efforts by making use of social media analytics. As 2020 progressed, the Covid19 epidemic became the most talked-about topic on Twitter (Cinelli et al., 2020). This research used social media analytics to examine the information distribution pattern and social media tactics of the leading worldwide container logistics companies in this age of global immobility. One drawback of adopting machine learning-based prediction models for univariate CT forecasting is the paucity of relevant published work. It is also clear that the predicting of CT and the investigation of the mechanisms controlling CT are two distinct areas of research. Yet, there is little discussion of the possibility of using explanatory factors in CT port predictions. To the extent that the CT forecasting literature incorporates explanatory variables, they are almost often macroeconomic or port-specific in nature. In conclusion, machine learning has not been applied for CT forecasting while considering the influence of external variables, despite its superior performance and broad application in time series forecasting. Indicators of BC acceptance have received the bulk of the attention in the research, although there are few examples of BC implementation in CSC. Unfortunately, there is a dearth of material on the implementation of BC in the supply chain, and much less about its potential impact on the container transportation industry. In addition, although there is a wealth of information on BC's authentication and transparency possibilities in the banking sector, there is far less discussion of how BC can meet the needs of B2B markets like CSC. What role may BC play in promoting long-term viability? This allows us to provide a succinct summary of the identified research voids: There is a lack of literature on the potential of incorporating explainable variables to predict container throughput, a dearth of literature on applying a deep learning-based forecasting model to predict container throughput, and sector-specific blockchain studies that could improve the interdisciplinary field's understanding of the technology. The following research questions are developed based on the research trajectories gleaned from the literature review and the junction of the identified research gaps with the subject of the present study: The first question we'll answer is: How can we better predict the throughput of containers at CSC? Second, what concrete steps may be taken to enhance CSC's operational efficiency by using the potential offered by blockchain technology? Using these two research questions as a starting point, the following goals are developed: First goal is to create a univariate, multivariate model for predicting container throughput using deep learning. Second, we need to learn how to put blockchain technology to work in the container supply chain and logistical operations.

4. CONCLUSION

This proposed work presents a comprehensive literature analysis on the supply chain and logistics of shipping containers. To find out what's new in IT for CSC, a literature evaluation is conducted that focuses on the overlap between the fields of information systems and operations management. Many holes in the literature were identified as needing more investigation. After identifying the gaps in the existing literature, we developed our two study questions and offered our two research goals. In the next proposed works, the research conducted to address these concerns and realize these aims will be described.

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