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Review

Digital Twin Integrated Reinforced Learning in Supply Chain and Logistics

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Abstract: *Background*: As the Internet of Things (IoT) has become more prevalent in recent years, digital twins have attracted a lot of attention. A digital twin is a virtual representation that replicates a physical object or process over a period of time. These tools directly assist in reducing the manufacturing and supply chain lead time to produce a lean, flexible, and smart production and supply chain setting. Recently, reinforced machine learning has been introduced in production and logistics systems to build prescriptive decision support platforms to create a combination of lean, smart, and agile production setup. Therefore, there is a need to cumulatively arrange and systematize the past research done in this area to get a better understanding of the current trend and future research directions from the perspective of Industry 4.0. *Methods*: Strict keyword selection, search strategy, and exclusion criteria were applied in the Scopus database (2010 to 2021) to systematize the literature. *Results*: The findings are snowballed as a systematic review and later the final data set has been conducted to understand the intensity and relevance of research work done in different subsections related to the context of the research agenda proposed. *Conclusion*: A framework for data-driven digital twin generation and reinforced learning has been proposed at the end of the paper along with a research paradigm.

Keywords: digital twin; data-driven technology; lean manufacturing; supply chain 4.0; reinforced learning; simulation modelling; prescriptive analysis; systematic review

1. Introduction

Digital twin technology creates relatively close connectivity between both the virtual and physical worlds, allowing you to monitor and command systems and components remotely. Moreover, it is now possible to run simulation models to test and forecast resource and process-related changes in various "what-if" scenarios. Hence, organizations are now getting significant benefits from digital twin technology that assists in mapping and analyzing details related to operations performance, product and service innovation, and shorter on time delivery [1,2].

The above-mentioned concept is one among the Industry 4.0 tools. Industry 4.0 is defined as the digitization of industrial processes, which incorporates the digitization of data as well as physical attributes [3]. Industry 4.0 is a tool that enhances the technological maturity level of any organizational system that allows for the adoption of digitalization, integration, and automation in the production and supply chain network [2,3]. Furthermore, the fourth industrial revolution is centered on vertical and horizontal integration of the value chain. Businesses can only sustain their market position in an increasingly competitive market by leveraging the benefits of synergy between production management and logistics [4]. The benefits are realized through logistically integrated production management, including the design of the information system required for planning and execution [5]. Creating a near exact twin of a process or product with well-defined parameters and variables is digital twin. Simulation modelling is the tool to accomplish a digital twin [2]. There have been extensive studies where simulation modelling and the digital twin approach have been applied to study and analyze various operations of production and supply chain systems and measure how they impact organizational performance and development as a whole [6]. However, there are still minimal insights and implications on the results obtained when digital twin technology is assisted with various other I.R 4.0 tools [7]. Currently, various studies have focused on the 'Know-How' procedure that could help us build a descriptive model with historical data and conduct only a what-if analysis by changing the variable values for certain operational parameters in the simulation model [8]. Instead of historical data, efforts are being taken to capture and retrieve real-time data using the internet of things and big data technology to feed and simulate a prebuilt digital twin prototype mother file [9]. In this course of action, several disruptions, buffers, delays, and challenges are met in the real-time scenario where solutions for these challenges can also be assigned. Over a course of period these actions can help create a series of patterns (scenario vs. solution) which can be useful to build a prescriptive analytics platform. The authors of this study are keen on studying the development of research in the above-mentioned theory. Authors argue that this combination of digital twin and machine learning has largely been utilized in the medical field and but less researched from the perspective of production, supply chain, and logistics.

Therefore, this study aims to conduct a systematic review of the literature to systematize and study the research findings and implications in the area of digital twin and its benefits when it is coupled with reinforced machine learning to improve production logistics and the supply chain. This research will answer the following research questions: RQ1) What are the applications of digital twin simulation modelling in Supply chain and logistics? RQ2) What is the impact of digital twin and reinforced machine Learning on supply chain and logistics? RQ3) What are the prospects and scope for prescriptive modelling in supply chain and logistics? How will that ease the process of building a decision support system for a supply chain or logistics 4.0? This paper has discussed the research problem and purpose of study in the introduction part followed by a state-of-the-art literature review discussing past research work and gaps. Based on the study, the authors have proposed a conceptual framework in the discussion part and concluded research findings and implications.

2. Literature Review

The digital transformation promises newer opportunities. However, only fewer companies can set up Industry 4.0 based production systems [10]. The fourth industrial revolution had an impact not just on the manufacturing sector, but also on the supply chains that supported it. Industry 4.0 can only become a reality if logistics can provide the necessary input components to production systems at the proper time, quality, and location [11]. However, this can only be accomplished by using new technological solutions to efficiently design and manage a more coordinated material flow. Industry 4.0 technology adoption is becoming increasingly vital for businesses to optimize their manufacturing processes and organizational structures. Companies, on the other hand, sometimes struggle to create a strategy plan with newer business models. For a Logistics 4.0 transformation, the firm's tendency toward logistics 4.0 is determined by the existing use of technologies in the logistics process, as well as the amount of investment towards innovation [12].

Nonetheless, there are several obstacles to overcome when implementing Industry 4.0. For example, a lack of technological infrastructure makes implementation difficult. Furthermore, there is a scarcity of professionals and knowledgeable staff in this field who can establish a new system or renovate an existing one to achieve the best results [13,14].

2.1. Relationship between Logistics 4.0, Supply Chain 4.0 and Industry 4.0

IR 4.0 has led to the digitization in supply chain and logistics has made way for the evolution of logistics 4.0. Various tools and technological settings from the IR 4.0 have been adopted in the supply chain and logistics setting or environment to leverage the benefits. Digital twin technology offers risk free scenario analysis by developing a predictive and prescriptive decision-making platform for the industry players and it is one of the core technological tools in IR 4.0 [11].

Basically, logistics is the sub-component of supply chain and supply chain is the sub-component of production management. A digitally equipped supply chain platform is the backbone for Industry 4.0 to function. I.R 4.0 tools equip the supply chain and logistics processes such as inbound logistics, warehouse management, intralogistics, outbound logistics and logistics routing, etc. I.R 4.0 based protocols and tools such as Smart data management, Internet of things, cloud computing and Blockchain accelerated the supply chain and logistics processes to greater extent. These create an automated, intelligent and increasingly autonomous flow of assets, goods, materials and information between the point of origin and the point of consumption, and the various points in-between are key. Supply chain logistics processes become more efficient, effective, connected, and agile/flexible in order to meet the needs of market [7,10–12].

Logistics 4.0 sounds similar to the concept of I.R 4.0. Instead of referring to the digitalization of industrial sector and processes it refers to the digitization of the physical elements and mobility. Moreover I.R tools have improved the visibility, imparted smart utilities, and adopted IoT in logistics. A state-of-the art logistics 4.0 scenario refers to the condition in which it becomes capable of collaborating and integrating with Industry 4.0 procedures and systems. Logistics 4.0 seems like a lucrative value-added proposition for all the businesses that wish to drift away from the complexities of a global supply chain creating supply chain transparency, automation, and real-time tracking [10–13].

2.2. Digitalization of Supply Chain and Logistics

Previous conventional supply chain and logistics processes in the industrial scenario had huge paperwork and manual interference. Recent inclusions such as data warehouse and SAP systems have revolutionized the way in which shop floors, warehouses and logistics entities work [12,15]. The static nature of visualizing a supply chain network needed a dynamic way to view it for better decision making, especially the current and future processes related to supply chain and logistics. It is now slowly possible only through effective digital transformation of the supply chain and logistics. Digital transformation is a key driver for Industry 4.0 that creates digitalized, interconnected, smart supply chain, and logistics [15,16]. In global supply chains, it is obvious that countries and logistics providers need to achieve a competitive advantage in terms of digitalization. However, still more studies should focus on measuring the potential for innovation to improve logistics efficiency [17]. In this context, particularly the term 'Logistics 4.0' receives growing attention, in recent years, which in a way accentuates that logistics as a central function plays an important role within the digital transformation of the manufacturing sector and thus, the underlying Industry 4.0 vision [18]. They are built with data-powered digital systems such as the internet of things, big data, and blockchain platforms with hyperledger [19]. However, the environmental issues in the supply chain should also be taken into account [20].

One such example is the digital learning factory that has been built by the Research Center of Vorarlberg University of Applied Sciences for educating students and employees of industrial partners by devising learning scenarios and courses addressing a wide variety of topics related to Industry 4.0 and showcasing the best practicing platform for digitalization. In addition, novel methods and technologies for digital production adopt cloud-based manufacturing, data analytics, and digital twins.

2.3. Real-Time Data-Driven Simulation Modelling

Use of historical data is becoming outdated and practitioners are looking for real-time data. Therefore, the demographic data acquisition from different supply chain players or stakeholders can also be utilized to obtain information such as the location of truck routes, distribution centers, retail stores, and individual consumers to understand the logistic systems [21]. These data can be directly fed into the Enterprise Resource Planning (ERP) database and production system database to generate a usable XML visual basic file that can be fed into the simulation software to create a digital twin.

To bolsters this, Goodall et al. (2019), [22] constructed a data-driven simulation model to predict material flow behavior in remanufacturing processes by using data from digital production systems (e.g., databases, traceability systems, process plans) to update and automatically modify simulation constructs to reflect the real world or planned system. The information was gathered through a Radio Frequency Identification (RFID) traceability software platform at the factory. Tannock et al. (2007), [23] applied the same concept in the supply chain of a civil aerospace sector. Qiao and Riddick (2004), [24] used a neutral information representation tool based on the extensible markup language (XML), to acquire information integration and exchange along supply chain applications. Similarly, mass customization in manufacturing and supply chain needs data integrated simulation systems. Qiao et al. (2003), [25] built a neutral model of shop information, based on the XML, to exchange data between simulations and perform analysis according to the demand fluctuations in the shop floor.

The product, product family, and related logistic resources like a truck, carriers, distribution centers, production facilities, warehouses can be presumed to be agents that can help create an agent-based model and replicate the behavioral pattern of the supply chain model. Another tool that can be integrated within a Discrete Event or Agent Based simulation models is the geographical information systems that allow use of the geographical maps with exact coordinates. This is further applied to allot location and routes for distribution centers, suppliers, trucks, etc. Product routing, supply chain optimization, Greenfield analysis can also be done using Geographic Information Systems (GIS) acquired from the logistics route database [26].

Discrete Event Simulations is used to adapt and mimic warehouse operations from the producer's perspective (Finished Product Des-patch & Product Recall), and a system dynamics model can be integrated to display managerial decision making, consumer behavior, and cost associated with these operations [6]. As a result, an integrated or hybrid modeling technique is utilized to virtually represent the dynamic nature of logistics models in terms of functionality as well as the cost incurred. Hybrid simulation modeling can precisely capture complex behavior and changes in model design. Typically, simulation is a representation of a system that is either going to happen in the future or is already present. As a result, a data-driven decision-support system combined with IoT connectivity will aid in feeding real-time data into a virtual real-time prototype [27]. A centralized SCADA (Supervisory Control and Data Acquisition) system acts as the core data hub [28]. As a result, these tools have enabled simulation modeling to obtain data from real-time data warehouses, resulting in a logistics 4.0 environment. As a result, data-driven simulation modeling generates scenario-based patterns that are employed by machine learning algorithms to instruct the models to react to previously established patterns and ascertained solutions.

2.4. Applications of Reinforced Learning in Supply Chain and Logistics

According to Meng at al. (2013), [27] there are several methods to set up a data-driven feed to simulation setting. One among them is generating XML visual basic code that can feed in the data required for the software given that the software is capable of receiving it. The inclusion of machine learning to build predictive analysis to enable automated logistics route optimization and decision making are enabled with a series of datasets that are utilized to build a descriptive, predictive, and prescriptive analytics platform with the help of regression/correlation-based supervised machine learning (deep learning) algorithms. This action is further validated to and predict behavioral patterns [29,30].

Logistics 4.0 and its self-perception can transform and strengthen conventional logistics. Logistics has been a central pillar of the supply chain for the industry. Extremely competitive and volatile logistics markets and large logistic networks need new approaches, products, and services. Today's customer behavior is leading to new strategic problems and opportunities. For that, the idea of the cyber-physical system (CPS), wireless networks, the Internet of Things and Services (IOT&S), Big Data/Data Mining (DM), and cloud computing, etc., seems to be the possible technological answer. Its consequent application ultimately leads to the need to revisit some core principles of conventional logistics [18,31]. To connect end-to-end logistics networks and meet complex manufacturing goals, it is very essential to tap the benefits of elements such as IoT (Internet of Things), digital twin simulation models, advanced robots, big data analytics, and virtual/augmented reality [32].

A logistic system needs to be optimized from both inbound and outbound that is possible by intelligent systems, embedded in software and databases from which relevant information is provided and shared through the Internet of Things (IoT) systems, to achieve a major automation degree by creating a network where all processes can communicate with each other, and enhance analytical potentialities throughout the supply chain. This promotes a significant decision-making standard and reaches top quality and becomes more and more flexible and efficient in the near future [33]. Song et al. (2020), [34] applied simulation integrated reinforced learning to study the percentage increase of ride-sharing in taxi service. They used taxi data from Seoul (South Korea) to determine optimal surge rates for ridesharing services over a specific period. The reinforced learning strategy based on centrality that governs the probability of the drivers' destination decision was used. Furthermore, passenger waiting time mediated the reward function.

Shen and Dai (2017), [35] applied the same principle in the container ship controller systems with neural network technique. Abdelghany et al. (2021), [36] introduced an innovative methodology for developing itinerary choice models (ICM) for air passengers. A reinforcement learning algorithm looks for the values of the itinerary choice model's parameters while maximizing a reward function. The negative difference between the estimated and observed system metrics is used to calculate the reward function.

Furthermore, Cavalcante et al. (2019), [37] proposed a new approach to analyze the risk profiles of supplier performance under uncertainty by combining simulation and machine learning integrated digital supply chain twins. These twins improved resilience by learning and designing risk mitigation strategies in supply chain disruption models, re-designing the supplier base, or judging the most important and risky suppliers. Similarly, more studies should be focused on the development of a state-of-the-art IoT-assisted embedded data-driven gateway that feeds online data to run the prebuild hybrid simulation models or digital twins. All the required parameters/variables to simulate the logistic model's dynamic complexity in real-time will be set up in the model to connect to their respective data and create simulation runs. By knowing the rubrics and dynamics of the logistic model, an optimized real-time value-focused application platform can be suggested for future research. Disruptions and related solutions (rewards) are applied to the models that are further integrated with a reinforced learning algorithm that captures the patterns of disruptions and give solutions to the same disruptions. Human intervention is avoided and artificial intelligence takes over.

This research approach can widen up the scope and give insights in building sophisticated AI-based decision support systems for future logistics 4.0. Various real-time industrial problems in the area of (1) Multi-mode transportation network optimization [38], (2) Truck route network scenario planning and optimization [39], (3) Smart Warehouse Bin Pick and Drop [6], Forklift Route Planning and Throughput, Automated Rack Storage and Retrieval [40], and (4) Multiple Criteria based Smart Conveyor Design [41], etc.

Strategic and resilient simulation models or digital twins appear to be an efficient and cost-effective tool for visualizing problems, proposing solutions, and practicing risk-free testing. They can virtually forecast optimal network design, inventory management methods, supply and distribution systems, logistics (micro and macro), and other associated systems [42,43]. Even though demand-specific uncertainties like work in process time, lead time, supply chain queues, delays, etc., can easily be projected using a digital twin [44], there is a need for perfect real-time data monitoring systems [45]. The manual data feed of historical data following the know-how trend has become old. A stochastic mode of what-if analysis with real-time online data is currently needed to analyze disruptions and measure the resilience of a system [46,47]. To attain this, simulation modelling are integrated with IoT to provide dynamic and virtual supply chains along with traceability and tracking options [48]. IoT-based modelling allows supply chains to use virtualizations to actively assist manufacturers in grappling with perishable products, volatile supply fluctuations, safety, and sustainability specifications. Virtualization allows supply chain members to track, manage, schedule, and automate logistics networks remotely and in real-time over the Internet, focusing mainly on physical reality instead of post-data observation [49,50].

While the latest revolution on digital transformational provides new opportunities. Logistics models are now re-evaluated by data-driven platforms. Extracting insights from operational data assists in predicting uncertainties and reduce inefficiencies in logistics operations by making them more resilient and sustainable [51]. But still, these are again just know-how digital twins at that point in time. However, it is also important to measure their behavioral dynamics when subjected to disruptions. Reinforced machine learning has great potential here to absorb humungous patterns of data and create a prescriptive analysis platform for logistics and build better decision support systems.

2.5. Applications of Digital Twin in Macro Logistics

Reliable plans to outline the trucks' routes are feasible by flexible and strong data-driven decision-making processes both at the operational level or real-time. IoT devices have the capability to enable this with ease. A simulation-based What-if scenario is generated to simulate, predict, optimize, project, and measure resource performance [52]. Global positioning system (GPS) based IoT devices are capable of collecting a large amount of data that were not fully utilized to optimize reaction times, a stochastic truck traveling speed previously. This data can act as a direct feed to the simulation model to allow risk-free truck route optimization according to the process constraints [53]. Simulation strategies like discrete event simulation have been widely used to design flexible and optimal resources. Previously, Meng at al. (2013), [27] developed a Unified Modelling Language-based formal information model to generate simulation models via pre-built Petri nets to address equipment scheduling issues. In another case, a severe traffic problem related to efficiency in urban ports was addressed by Heilig et al. (2017), [54] with the same method in which an algorithm was developed to build a cloud-based decision platform to consider contextual data, including traffic data and the current positions of trucks allowing ports to utilize potentials of digitalization and optimization issues.

2.6. Application of Digital Twin Technology in the Warehouse Operations (Micro + Macro Scenario)

It can also be applied extensively in warehouse-based scenarios. The best example is the optimization of automated modular conveyor systems in warehouses facing bottlenecks. The unpredictability and intricate dynamics of the process can be captured by time-based simulation modelling. These models are exposed to various scenarios after verification and validation. In addition, if this is made completely data-driven, a cost-effective approach is given to increase performance. This is the future of a stable standalone system of decision support enabled by dynamic digital twin recreations [55].

To mention a few, Sahay and Ierapetritou (2013), [56] formulated a hybrid simulation modelling approach by combining an iterative model with an agent-based simulation model which can decide toward an optimal allocation of resources subjected to multiple problems and constraints. Industry 4.0 has paved the way for a world where smart factories will automate and upgrade many processes through the use of some of the latest emerging technologies. It can ease the automatable and tedious tasks, like the ones performed on a regular basis for determining the inventory and for preserving item traceability [57,58]. Kim et al. (2020), [59] formulated optimal cut-off and pick-up time in the warehouse as per the customer order responsiveness through priority-based job scheduling using flow-shop models that can assist warehouse managers in decision making. The application of stochastic simulation models for uncertain real-life operational environments contributes to the practical gap and novelty.

To conclude on this case, a real-time industrial warehouse problem can be addressed, or a prototype warehouse bin pick up and storage system in the logistics 4.0 lab that is included with few modifications along with problem definitions and solutions. The insights from the study conducted by Fragapane et al. (2019), [60] provided directions in terms of the research objective and also use the process parameters that were used in the statistical model. These methods can tackle many distribution warehouse issues without the restrictions of traditional tools. Hybrid Smart Simulation can abstract distributed autonomous entities that can interact with each other and their environment through space and time, allowing to capture a lot of resource relation attributes such as work time allocation of resources, automated guided vehicle (AGV) work scheduling, congestion (buffer) wait time, process/cycle times, Forklift throughput, worker and machine speeds, resource block behavior, Bin or Rack Storage, Designing Artificial Storage and Retrieval System, etc.

Moreover, a hybrid modelling approach can also be adopted to virtually visualize the dynamic nature of the system or logistics model covering all the functionalities. Complex behavior and changes in model design shall be precisely captured by hybrid simulation modelling. Usually, simulation is a display of a system that is either going to happen in the future or that is already there. So, a data-driven decision support system + IoT integration gateway module will be installed here in feeding real-time data to obtain a virtual real-time prototype. Later, these data patterns are utilized to build a predictive analytics platform with the help of reinforced/supervised machine learning algorithm. A real case logistics system from the industry shall be first recorded and tabulated for primary data taking either Case A or B systems into account.

For example, the product, product family, and logistic resources like a truck, carriers, AGVs, and Conveyors, etc., are presumed to be agents to replicate the behavioral pattern of the system under study. IoT devices assist in obtaining real-time data by directly retrieving data from the resource blocks mentioned above to the embedded cloud server. If not, it can also be retrieved from the Enterprise Resource Planning (ERP) database and production system database to generate a usable XML visual basic or CSV file that are fed into the simulation software. However, the latter has technological constraints if the host firm does not have this setup.

The geographic information system feature in the simulation modelling software shall assist in planning the optimal positioning of the distribution centers, transport routing, milk runs, product routing, and supply chain optimization. After the completion of an empirically verified digital twin, the parameters for disruptions and respective solutions shall be included in the models to analyze different scenario patterns. These patterns are separately retrieved to build Reinforced Learning Algorithms that help create a prescriptive analytic platform that acts as a stepping stone for logistics 4.0 decision support systems.

There are several methods to set up a data-driven feed to simulation software. One among them is generating XML visual basic code that can feed in the data required for the software given that the software is capable of receiving it [27]. Therefore, the series of datasets are utilized to build a descriptive, predictive, and prescriptive analytics platform with the help of regression/correlation-based supervised machine learning (deep learning) algorithms. The main aim of this review is to study past research on this idea and its development and later systematize the data set for better implications.

3. Methodology

The Scopus database was selected for the data set retrieval since it consists of a wide range of published data in large volume compared to other databases. A strict keyword search strategy was applied to cover papers on both 'digital twin' and 'supply chain' from the database. These keywords were added in the title-abstract-keyword option in which both journal and conference-related papers published in the English language were selected. Initially, 154 items were identified. Duplicates were removed and articles with only close relevance to the application of digital twin in the supply chain were identified by thoroughly reading the title and abstract of all the papers. The authors finally identified 96 journal articles and conference proceedings that met the criteria. The search strategy followed the Prisma systematic review protocol. Papers with commendable research and implications were identified by the authors to conduct a systematic review. The keyword search and criteria applied are given below and Figure 1 portrays the methodology adopted for this systematic review adopted from.

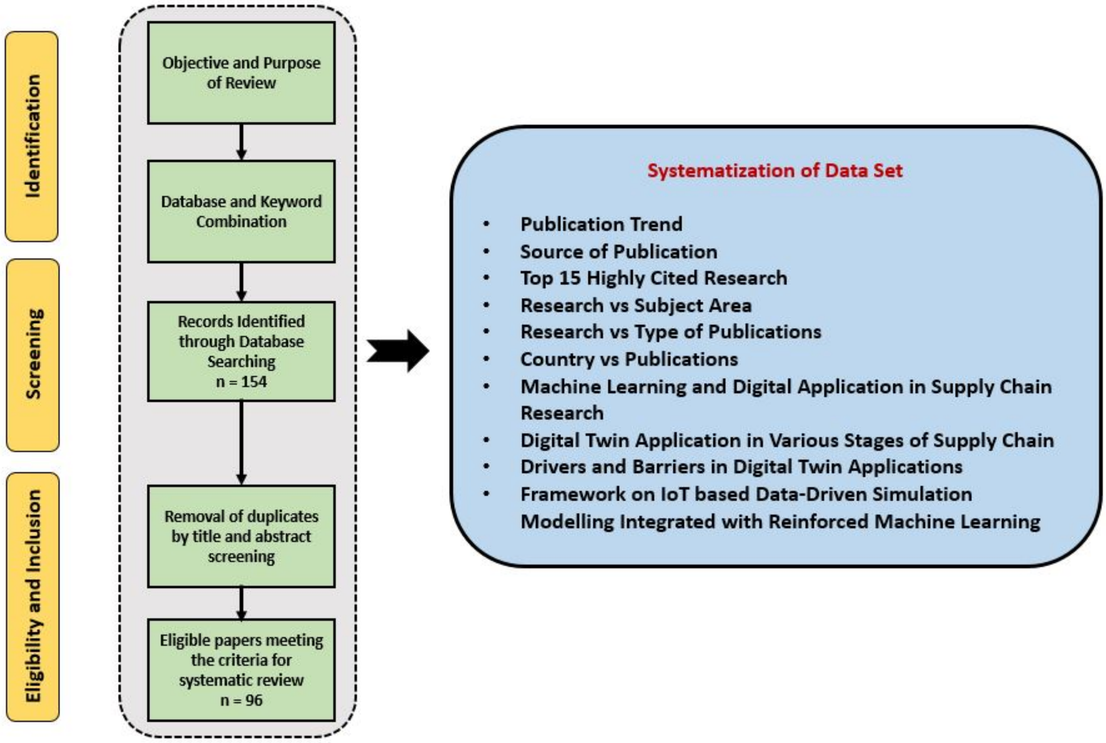

Figure 1. Methodology.

(TITLE-ABS-KEY (digital AND twin) AND TITLE-ABS-KEY (supply AND chain)) AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "cp")) AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (SRCTYPE, "j") OR LIMIT-TO (SRCTYPE, "p")) AND (LIMIT-TO (SUBJAREA, "ENGI") OR LIMIT-TO (SUBJAREA, "COMP") OR LIMIT-TO (SUBJAREA, "BUSI") OR LIMIT-TO (SUBJAREA, "DECI") OR LIMIT-TO (SUBJAREA, "ENER") OR LIMIT-TO (SUBJAREA, "ENVI") OR LIMIT-TO (SUBJAREA, "SOCI")).

4. Results

The trend in publication as shown in Figure 2 clearly shows that the notion 'Digital twin' got its popularity in the year 2019 and was studied extensively in 2020 and 2021. However, the publications in (2021–2022) subject to change and it is not the final data (Note: In Figure 2, the 2021 (red dot) and 2022 (yellow dot) are incomplete and the counts were calculated only until October 2021).

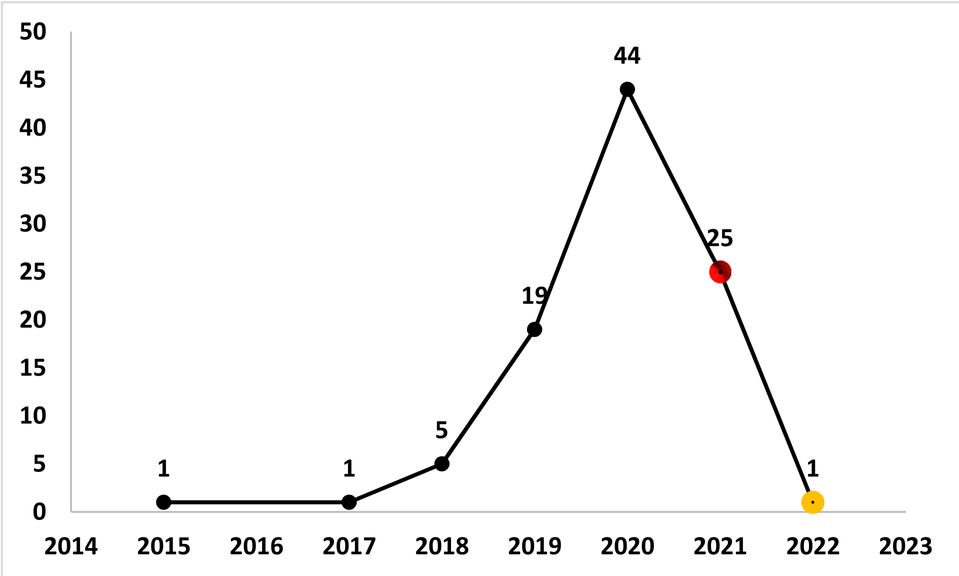

Figure 2. Year vs. Number of Publications.

Simulation modelling (digital twin) has become one of the pillars of Industry 4.0. The technological insights this tool brings that ease the decision-making aspect in the business area are phenomenal. The authors further tabulated the number of publications based on the sources which are shown in Table 1 (only Journal sources). The Journal sustainability, applied sciences, IEEE access and International Journal of Supply Chain Management, Computers in Industry, and Transportation Research Part E: Logistics and Transportation Review have published quality papers on this area.

Table 1. Source of publication (Journals).

S.No	Journal	No of Publications
1	Sustainability (Switzerland)	5
2	Applied Sciences (Switzerland)	4
3	IEEE Access, EAI Endorsed Transactions on Energy Web, Energies, International Journal of Supply Chain Management, Computers in Industry, Transportation Research Part E: Logistics and Transportation Review, Academy of Strategic Management Journal	2
4	Mobile Networks and Applications, Computers and Chemical Engineering, International Journal of Web Engineering and Technology, Recent Patents on Mechanical Engineering, Entrepreneurial Business and Economics Review, Resources, Conservation and Recycling, IET Collaborative Intelligent Manufacturing, Operations Management Research, Advances in biochemical engineering/biotechnology, International Journal of Mathematical, Engineering and Management Sciences, International Journal of Pavement Research and Technology, Industrial Management and Data Systems, Food and Bio products Processing, International Journal of Integrated Supply Management, Case Studies on Transport Policy, International Journal of Production Research, Sensors (Switzerland), Production Planning and Control, Journal of Cases on Information Technology	1

Table 2 shows the top ten highly cited authors and their corresponding research work and targeted research area. Each data set was closely reviewed and the subject area of research was tabulated and plotted as Figure 3 which also portrays the percentage of type of publication (Journal or Conference proceeding). Conference publications are sought by the researchers and given equal importance to project new ideas, frameworks, and research agendas. A huge amount of research has been seen in the Engineering and Computer science area. Still, the scope for applications and leveraging the benefits of digital twin technologies has not been seen in energy, environmental sciences, social sciences, business economics, and decision sciences. In the country-wise numbering, United States leads the list followed by Germany, Italy, Russian Federation, United Kingdom, France, and Switzerland as shown in Table 3.

Table 2. Area of Research Targeted vs. Author vs. Research work done (top 15).

Author	Area of Research	Research Done	Number of Citations
[61]	COVID 19 supply chain disruption (Global Supply Chain)	Developed simulation models to articulate epidemic-related aspects and their relevance to supply chain disruption risks.	381
[37]	Machine Learning and Supplier Selection	Forecasted the disruption probabilities to assess the risk profiles of supplier performance under uncertainty by applying machine learning and digital supply chain twins.	89
[2]	Supply chain disruption in Industry 4.0 using digital twin	Applied digital supply chain twin in supply chain risk management and related disruptions to allow predictive and reactive decision making.	86
[62]	Supply Chain Resilience in COVID 19 pandemic	Modelled the ripple effect of an epidemic outbreak in the global supply chain considering various aspects of disruption.	60
[63]	Additive Manufacturing and Digital Twin	Developed an additive manufacturing and digital twin technology in aircraft production and inventory management.	59
[64]	Manufacturing and remote sensing	Proposed remote testing and maintenance of manufacturing equipment with the support of digital twin technologies during natural disasters and other scenarios.	25
[65]	Construction engineering	Presented a novel proof-of-concept framework for implementing building information modeling (BIM) Digital Objects (BDO) to automate construction product manufacturers' processes and augment lean manufacturing using digital twin technology.	24
[66]	Blockchain technology	Demonstrated the implementation of a portable, platform-agnostic and secure Blockchain Tokenizer for Industrial IOT trustless digital twin applications that were tested on two supply chain scenarios.	23
[67]	Product Development	Studied data-driven digital twin technology in product lifecycle management (PLM).	20
[68]	Cold Supply chain	Developed a digital fruit twin, based on mechanistic modelling and simulated the thermal behavior of mango fruit throughout the cold chain, based on the measured environmental temperature conditions.	17

The authors were keen on studying the integration of machine learning with simulation modelling and found eight research works with their respective research areas as shown in Table 4. Authors reviewed dataset on machine learning integrated digital twin applications and tabulated in Table 4 to get insights for RQ2 and 3. Later the same review method was adopted to tabulate Table 5 by dividing the data set into different stages of the production supply chain. Authors reviewed dataset on the application of simulation modelling on different stages of supply chain to get insights for RQ1 and 4.

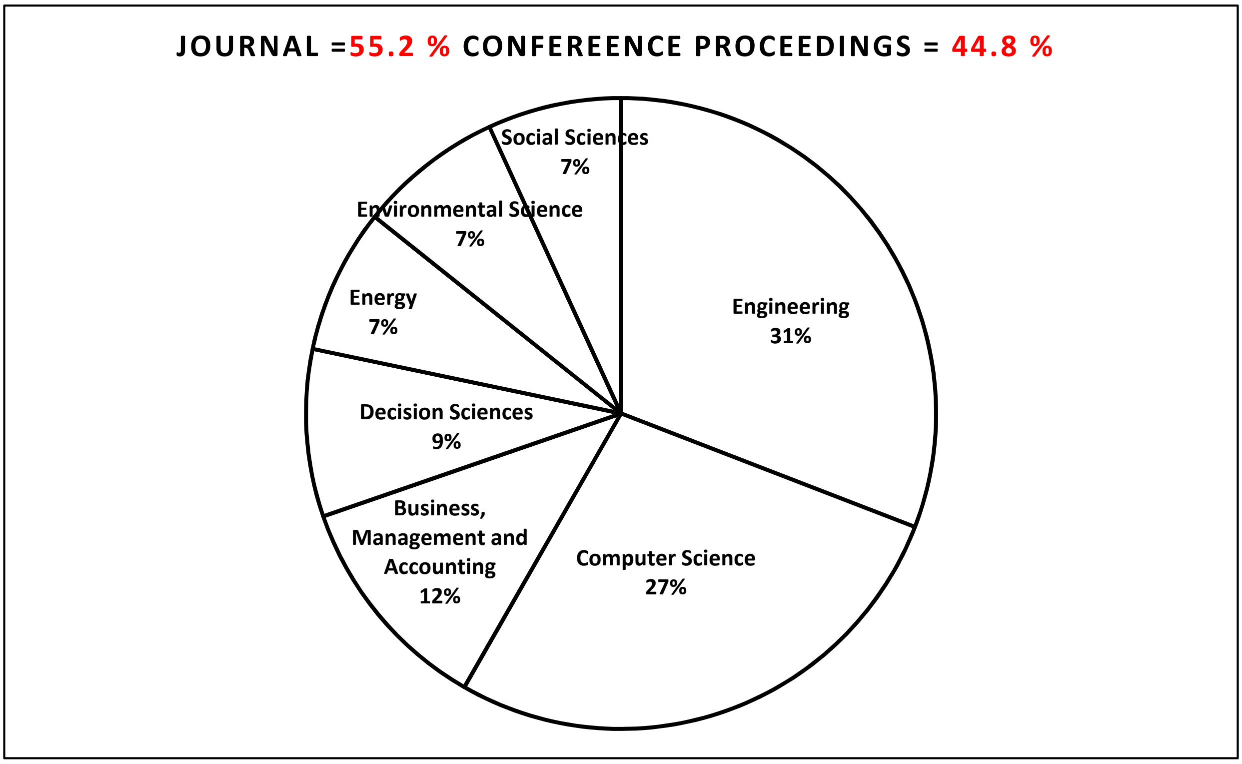

Figure 3. Document vs. Subject Area and Document vs. Type.

Table 3. Documents vs. Territory.

Country	Number of Documents
United States	17
Germany	15
Italy	10
Russian Federation, United Kingdom	8
France	7
Switzerland	6
Australia, China, Hungary	5
Mexico	4
Brazil, Netherlands, South Africa	3
Finland, Norway, Romania, Singapore Slovenia, Spain, Sweden	2
Austria, Belgium, Estonia, Ethiopia Greece, Hong Kong, India, Japan Kazakhstan, Latvia, Lithuania Macao, New Zealand, Poland Portugal, South Korea, Turkey United Arab Emirates	1

Table 4. Machine Learning integrated with Digital Twin in Supply Chain.

Author	Research Work	Research Area
[69]	Machine learning methods were evaluated to estimate smooth and unpredictable demand in a real-world use case scenario, and a set of measures and requirements were proposed to gain a full comprehension of demand forecasting model performance.	Demand Forecasting in Automotive Sector
[39]	Presented a revolutionary data-and-model-driven architecture to enable urban distribution strategic planning, allowing stakeholders to construct warning systems and make the optimum use of available assets by combining optimization, machine learning, and simulation models.	Urban Mobility Planning
[70]	Using a conceptual control strategy offering predictive tactical awareness for robot pelletizing cells, a model-driven DT setup with embedded simulation quicker than real-time was paired with a data-driven Digital Twin.	Robotics in Manufacturing
[71]	Created a physical distribution digital twin model with the goal of using it to manage trade system functions in collaboration with digital cyberspace.	Cyber trade
[72]	Employed real-time simulation and task scheduling algorithm to demonstrate how data from interconnected, unsupervised, and smart supply chains may be incorporated into the heterogeneous data ecosystems.	Supply chain and Industry 4.0
[37]	Created a hybrid approach that incorporates simulation and machine learning, and investigated its implications to data-driven decision-making help in robust supplier evaluation.	Supplier Management

Table 5. Application of DT in Different Supply Chain Stages.

Author	Procurement	Production/Manufacturing	Warehousing	Logistics and Transportation	Research Work
[73]	✓				Discrete event simulation was used to investigate the impact of the COVID-19 pandemic on food retail supply chains resilience.
[74]		✓			Developed a simulation model for a sterile pharma products factory line to investigate the sensitivity of steps involved, cycle design and batch change circumstances, multiple shift models, scheduling methodologies, and transportation failure risk assessments.
[68]				✓	Based on the measured environmental temperature conditions, a digital fruit twin based on mechanistic modeling was created to simulate the thermal behavior of mango fruit across the cold chain.
[75]				✓	In a multi-level Cyber-physical Systems structure, a cyber-physical logistics system (CPLS) was proposed that coordinated with the agent of the systems to give technical functionalities for the robust supply chain management.
[76]		✓			A method for automatically discovering manufacturing systems and generating appropriate digital twins to accurately assess system performance was proposed.
[77]		✓			Integrated Digital-Twin with metaheuristic optimization and a direct Simulink model for printed circuit boards (PCB) design and processing.
[78]		✓			Presented a case from the automobile industry and analyzed data exchange requirements using IoT, digital twin, and cyber-physical systems.

Table 5. *Cont.*

Author	Procurement	Production/Manufacturing	Warehousing	Logistics and Transportation	Research Work
[79]			✓		Proposed different identification approaches to combine and facilitate an efficient and reliable identification scheme for asset tracking in logistics using digital twin technology.
[39]				✓	Proposed a novel data-and model-driven framework to support decision-making for urban distribution to solve complex vehicle utilization problems and fleet cost.

5. Discussion

After a detailed systematic review and reading, insights in line with past studies have been discussed below in the following sections to answer the research questions. Furthermore, major barriers and scope for digital twin integrated with data-driven simulation modelling and digital twin technology is portrayed along with a conceptual and operational framework.

(RQ1) What are the applications of digital twin simulation modelling in Supply chain and logistics? (RQ2) What is the impact of digital twin and reinforced machine Learning on supply chain and logistics? (RQ3) What are the prospects and scope for prescriptive modelling in supply chain and logistics? How will that ease the process of building a decision sup-port system for a supply chain or logistics 4.0?

5.1. Applications of Digtial Twin Simulation Modelling in Supply Chain and Logistics

Simulation is a significant tool for analyzing supply-chain behavior, often in terms of throughput, cost, delivery reliability, variability, and risk. It allows potential model settings to be tested against potential upcoming supply-chain scenarios. The building and application of a model in traditional discrete-event simulation approaches is a complicated, multi-stage, iterative process. Such model configuration modifications are especially common when evaluating design possibilities for a large organization [23]. Several recent academic contributions have emphasized increasing process automation using built-in models. The information that describes the model's characteristics is stored in such a way that it is utilized directly by a modelling software to produce the necessary models, which is a fundamental aspect of such methods. Relational databases, such as SQL, are commonly used for this purpose, with XML schemas used to send the data to the simulation software. The procedure is further automated if the necessary data for the models are gathered from existing data sources, like a company's enterprise requirements planning (ERP) system. Bills of materials (BOM), resource capabilities, process timeframes, and customer and supplier information are examples of such data. Examples of data-driven simulation applications that make use of several commercial simulation programs have been provided [80].

Moreover, supply chain design is re-amended using data-driven modeling and simulation that can act as a decision-support tool. The data might be stored in the primary entity or in a "collaboration hub", an independent portal organization that allows interaction between partners in a larger enterprise. These data can be downloaded from the ERP system, saved in an appropriate file format to utilize the information to link elements and set parameters in the simulation model, which can be automatically generated. Nonetheless, a level of data validation is needed to be performed concurrently [3].

There are two ways to build simulations: modular simulation and data-driven simulation. Modular simulations provide general templated modules that may be reused to simulate the behavior of a given domain element using specialized simulation structures, which are often controlled using a Graphical User Interface (GUI). However, research is being conducted to simplify this to particular functions incorporating parameters related to reverse logistics and lean production [4].

Data-driven simulations are models that are fully parameterized, allowing data to be entered and changed outside of the simulation. Rather than relying on assumptions or manually timed operations, historical process data uses data gathered from shop floor activities to enter data into a simulation. This data is utilized in manufacturing simulations to calculate processing times and decision probabilities, as well as the variance in these outputs. These attributes generate an automated model generation module [7,81]. A self-contained software component that acts as an application programming language capable of data gathering, retrieval, and sorting can be written in an independent programming language to the simulation, allowing reuse within different applications. SQL and Python software are adopted in these areas [22]. This sub-section has discussed on the application of simulation modelling (digital twin) in supply chain and logistics gives brief answers to the RQ 1.

5.2. Barriers in the Application of Digital Twin

Companies need to assess if a suitable communications infrastructure is already in place for successful data collection before embarking on a digital twin initiative. Even if enough data is available, organizing and analyzing it to generate values will be a challenge. To prevent convoluting processes, it is critical to examine a firm's current digital capabilities. Similarly, maintaining software, developing simulations, and followed by constructive data analysis require a strategic approach. It is extremely challenging to find the assets and processes that have the most potential for value generation and then launch a pilot study. It is also difficult to model systems that encapsulate real-time work-in-progress as it evolves and scales over time. This necessitates a certain amount of IT up-gradation and maturity with interlinked simulation models.

5.3. Impact of Reinforced Machine Learning on Supply Chain and Logistics

ML outlines the importance of when to construct systems that develop themselves automatically over time. It is one of the most quickly expanding technological disciplines, straddling computer science and statistics and teetering on the brink of artificial intelligence and data science. Python modules, such as the Scikit-Learning module, can interface with a large variety of cutting-edge ML techniques for medium-scale supervised and unsupervised issues. Other packages, like Numpy, Matplotlib, and Pandas, are also used for data preparation, analysis, and presentation. Zero or missing values are seldom found in simulation results [70]. Usually, data in normal instances is likely to diverge from a well-behaved normal distribution, the supervised machine learning [SML] model does not employ any past information about system behavior to better reflect a realistic situation [37,82]. Nonetheless reinforced learning algorithm refers to the previous pattern of data to help in decision making [4].

Specifically related to this concept, [37] demonstrated Ad-hoc customer-supplier relationship management using a data-driven technique-based simulation modeling and completely unbiased supervised machine learning. The digitalization of industrial resources was regulated by the inclusion of an Internet of Things device, which provided synthetic data to train ML models. Additionally, the usage of rule-based systems incorporating various learning algorithms improved the performance of the system. This might imply that using learning subsystems via meta-learning could give even better results, especially when modeling in more complicated settings.

5.4. IoT Assisted Data Retrieval and Usage

IoT-based sensors that capture operational behaviors of resources and processes, as well as their functional properties, are required for the creation of a digital twin. Reliable and secure data transport from physical devices to the digital world is provided via communications networks. A digital platform that combines shop floor sensor data with high-level business data to function as a modern database server like enterprise resource-based software. Advanced machine learning algorithms are used to extract actionable insights from these data sources for data-driven decision-making. The level of sophistication and detail of your digital twin models depends on the availability and maturity of your IT infrastructure [27,29,30,37].

To uncover bottlenecks, improve operations, and reinvent product development, digital twin technology provides unprecedented visibility into assets and production. In the manufacturing sector, companies can instantly spot faults and variations in their operations thanks to predictive maintenance, which allows us to acquire a complete perspective of the health and performance of infrastructure. Spare component repair and replacement can be scheduled ahead of time to reduce time-to-service and avoid costly asset breakdowns. Predictive maintenance with Digital Twins can help OEMs generate new service-based revenue while also improving equipment reliability [83,84]. Reinforced learning integrated with digital twin can solve issues related to route mapping [85], warehouse lead time [86,87], demand forecasting [69], inventory planning [88], Orders Backlog Reduction [83], Logistical uncertainties & communication gaps [7]. The data-driven technology further enhances the scope by creating virtual real-time supply chain planning & optimization, capacity utilization/throughput rate, distribution and backlogs, better demand management, geographic route map integration, and estimation of financial and operational Performance Indicators This sub-section has discussed on the collective benefits through integrating digital twin and machine learning in supply chain and logistics that briefly answers RQ2.

5.5. Prospects and Scope for Prescriptive Modelling in Supply Chain and Logistics—An Operational Framework

After a thorough literature review, the authors propose a framework on how real-time data are utilized to generate data feed to the simulation model to create a real-time digital twin. This procedure can replicate the real-time scenario up to satisfactory levels [69]. These twins can mimic different problematic scenarios and corresponding responses that are fed by the human operator to overcome them. Later, this pattern over a period of time can be effectively captured, recorded, and retrieved to build a reinforced machine learning platform for smart decision-making in the supply chain sector. The authors propose a logic and framework on this context in Figures 4 and 5 below.

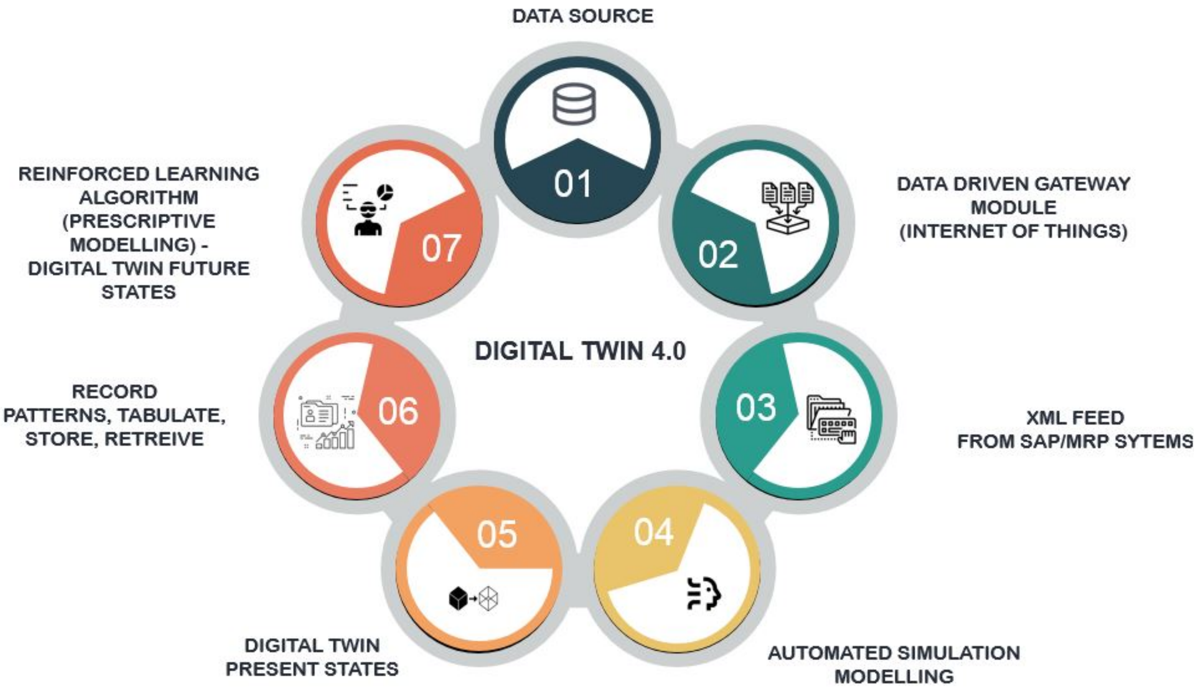

Figure 4. Data-Driven Digital Twin for Reinforced Learning.

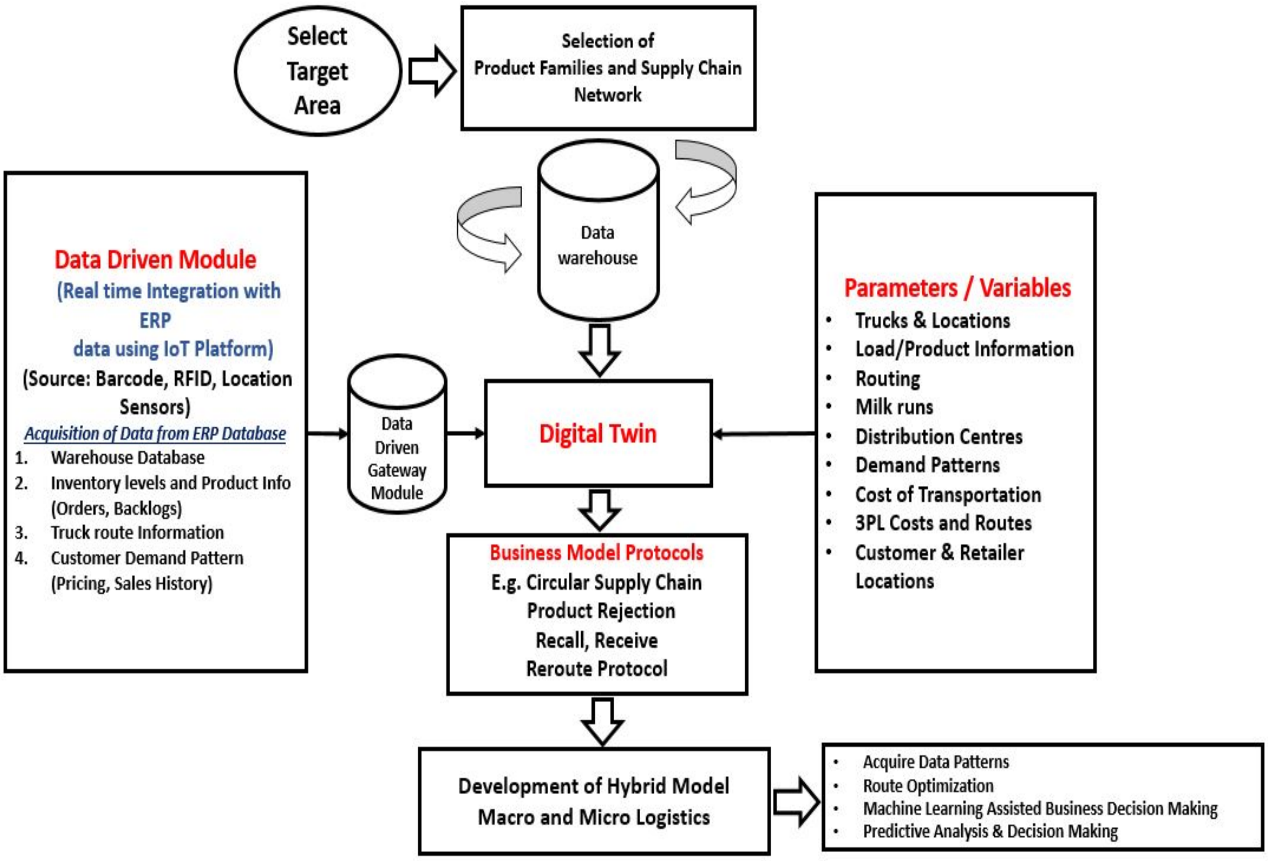

Figure 5. Digital Twin—Reinforced Learning Framework for Supply Chain and Logistics.

5.6. Applications of Reinforced Learning and Digital Twin in Micro and Macro Logistics

Revolutionizing logistics and supply chain management in smart manufacturing is one of the main goals of the Industry 4.0 movement. Emerging technologies such as autonomous vehicles, Cyber-Physical Systems, and digital twins enable highly automated and optimized solutions in these fields to achieve full traceability of individual products. Tracking various assets within shop floors and the warehouse is a focal point of asset management; it aims to enhance the efficiency of logistical tasks. Global players implement their solutions based on the state-of-the-art technologies. Small and medium companies, however, are still skeptical toward identification-based tracking methods, because of the lack of low-cost and reliable solutions. This paper presents a novel, working, reliable, low-cost, scalable solution for asset tracking, supporting global asset management for Industry 4.0. The solution uses high accuracy indoor positioning—based on Ultra-Wideband (UWB) radio technology—combined with RFID-based tracking features [79]. Therefore, authors have discussed on the future prospects of prescriptive modelling from a digital twin and reinforced learning context in supply chain and logistics that briefly answers to the RQ 3 and 4.

6. Conclusions

Previous studies are mainly focused on simulation modelling to understand only know-how procedure using historical data, but they do not explore real time simulation modelling or digital twin generation using IoT assisted real time data that can be fed into the simulation models to generate patterns of occurrences or scenarios. Studies must also focus on how this real time data patterns can be recorded to teach a machine learning algorithm to behave and function and act as a reinforced or prescriptive learning platform. This research area shall help greatly to revolutionize dynamic capability and decision-making level in the supply chain and logistics.

Moreover, the fourth industrial revolution also demands the same level of maturity in digitalization to ensure the transparency and integration of business processes and related value chain and the supply network. Firms can only thrive in the market by exploiting the proper and balanced vertical and horizontal integration opportunities that prevail in production management and logistics. Finding out that optimal integration point is very crucial to leverage the best of Industry 4.0 [5]. Modern information and computer technologies are the driving force to digitalize production logistics. Among them, the Internet of Things (IoT) plays a major role to connect the external data with the internal resources [15], which assists in the digital transformation of production and logistics into a digitalized, interconnected, intelligent factory with smart logistics [16].

Firms are striving to attain a competitive advantage by leveraging the benefits of smart logistics with a high-performance index. They are investing highly in data-enabled technologies and establishing proper interconnectivity and integration to ensure superior value creation and increase flexibility [89]. Industry 4.0-based production logistics outplay traditional production logistics in terms of productivity, flexibility, and costs [60]. These aspects make a supply chain into a hybrid supply chain 4.0 in which the atmosphere must have interoperability and information transparency technical assistance. Nothing but the analytical support by the system for humans in making decisions and solving problems. It denotes the ability to assist humans with tasks that are too difficult or physically risky for them to complete on their own. Furthermore, decentralized decision-making technology is the ability of cyber-physical systems to make simple judgments on their own and become as autonomous as feasible, especially in micro logistics facilities.

IoT offers dynamic 'reconfigurability' of supply networks, especially by re-examining service-level agreements with upstream and contracted suppliers; supply network design, towards achieving lean, agile, resilient, and green supply chains. In this context, logistics will be addressed under the term "Logistics 4.0". From a technological and in-line processes perspective, it must be noticed, the Logistics 4.0 aim is not to replace humans in their works, but to avoid inaccuracies and to have faster processes where the information is shared effortlessly in real-time. It will be always needed the involvement of people controlling the processes and taking control of any system failure. The intelligent data-driven hybrid IoT integrated simulation-based real-time logistics models backed up by a prescriptive analytic platform built with machine learning shall help attain optimized smart scenario planning for logistics 4.0. Integration of data-driven hybrid simulation modelling shall portray the digital twin of the system under study to understand the dynamics of risk, costs associated, wastes in the timeline and assist in generating numerous patterns with problems and solutions (along with the solutions, which would act as a reward parameter to feed into the reinforced learning algorithm). A state-of-the-art decision support system to enable logistics 4.0 for numerous applications are developed along with a predictive analytics platform built using machine learning algorithms. Different logistics systems shall give different implications.

However, recent strict regulations and competitive economics worldwide, and a growing number of companies are committed to a combination of good manufacturing practices along with automation to maintain the highest quality of the product [90]. Logistics 4.0, which is a primary entity or backbone of industry 4.0 can bring this revolutionary change. IoT integrated hybrid simulation-based approach shall provide detailed insights on the dynamic changes in the system on a real-time basis. Moreover, the data-driven gateway setup can provide optimal assistance to maintain resilience and sustainability in the system. These behavioral dynamics and corresponding decisions are tabulated to build a prescriptive analytic platform through a reinforced learning algorithm. Moreover, very little attention is given towards the digitalization of logistics 4.0 with a huge managerial and practical gap. This study shall also contribute greatly to the body of literature in the area of Logistics 4.0.

Innovation in the business model for sustainability and circularity is still fragmented. A dynamic capacity-based perspective analysis is required to resolve this problem and there is a lack of systematic solutions [91]. To build feasible and resilient smart, sustainable production and supply chain systems as functioning virtual models with socio-economic impact more mixed-method research methodologies are needed. Additional research work is needed to propose solutions to private or government bodies to develop a circular value chain and address citizens' day-to-day problems. The growing significance of novel technologies became apparent as well most recently by the COVID-19 pandemic [92]. Therefore, information technologies and related solutions play an active and crucial role in the provision of needed logistics and transport services. For instance, geographic information systems (GIS) and Big Data analytics can be applied to balance the supply and demand of limited material resources—e.g., medical supplies. Next to this, digital supply chain twins shall be used to support decision-making, since the first epidemic outbreaks. The effectiveness of a smart system directly relates to the level of technological readiness. Data driven digital twins backed by reinforced learning have revolutionary scope in the supply chain segment.

This study has reviewed the Scopus database only, however using this database we have explored a wide range of previous studies related to the topic of research. Nonetheless, there could be distorted or incomprehensive views which is a limitation of this study. Moreover, the keyword "digital twin" was included under the umbrella keyword "supply chain" and keywords such as "logistics 4.0" and or "manufacturing 4.0" were not used. However, authors have thoroughly gone through the initial dataset to filter the most relevant publications in line with the research agenda.

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