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Article

Generative AI for enhanced operations and supply chain management

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Abstract: In this paper, we will provide an extensive analysis of how Generative Artificial Intelligence (GenAI) could be applied when handling Supply Chain Management (SCM). The paper focuses on how GenAI is more relevant in industries, and for instance, SCM where it is employed in tasks such as predicting when machines are due for a check-up, man-robot collaboration, and responsiveness. The study aims to answer two main questions: (1) What prospects can be identified when the tools of GenAI are applied in SCM? Secondly, it aims to examine the following question: (2) what difficulties may be encountered when implementing GenAI in SCM? This paper assesses studies published in academic databases and applies a structured analytical framework to explore GenAI technology in SCM. It looks at how GenAI is deployed within SCM and the challenges that have been encountered, in addition to the ethics. Moreover, this paper also discusses the problems that AI can pose once used in SCM, for instance, the quality of data used, and the ethical concerns that come with, the use of AI in SCM. A grasp of the specifics of how GenAI operates as well as how to implement it successfully in the supply chain is essential in assessing the performance of this relatively new technology as well as prognosticating the future of generation AI in supply chain planning.

Keywords: Artificial Intelligence (AI); supply chain management; generative AI models; industrial applications

1. Introduction

Today the current intensified business environment requires suggestions and improvements to be made continuously for the establishment of competitiveness. It is imperative to note that the field in which operations and supply chain management (OSCM) is applied is a field that is being affected by technology. This is because this field has developed Generative Artificial Intelligence (Gen-AI) that is thought to shape decision-making, performance, and productivity.

Another category of AI that possesses the potential to generate content is generative artificial intelligence or Gen-AI. They achieve this by making conclusions and advocating for data from the real world. Based on the kind of training data that is fed to GenAI, the system is capable of generating other forms of material for example in writing like this text, visuals such as images, audio such as music, and even real-life simulations on a computer (Kumar et al., 2019), it is more focused on analyzing the learning data in terms of correlation to be able to recognize the trend, pattern, and structures that are closer to that of the human mind. That is why We agree with the statement that a Gen-AI variant with a large language model (LLM) is just here to type. One example of an LLM is ChatGPT which was developed by

OpenAI (Aydın and Karaarslan, 2022). There could or should be other forms of Gen-AI applications when new text is created out of the old libraries. Moreover, I would like to add that the generative AI models can be improved in case they are programmed to learn from all comments that they receive and new data fed in the system. The accuracy and capacity are bound to rise with time and this means that this opens up the model to a whole new level of artificial intelligence.

Gen-AI contains the sub-group of machine learning to develop new type of data rather than handling the existing data (Hassani and Silva, 2024). Applications of denoising have been highly promising across various fields, especially in the subcategories of NLP, CV, and arts. For example, OpenAI which was released published its GPT-3 model for natural language processing that showcased abilities in coming up with human-like text (Pokhrel and Banjade, 2023) which can be used in programs such as generation of tenders as well as natural language interfaces (Bozkurt, 2023). In CV generative adversarial networks (GANs) are applied for synthesizing realistic image (Cao et al., 2019) and they also outperform the traditional methods in the image synthesis and style transfer. Moreover, Gen-AI has been used to compose and design music and art pieces in different forms of artwork that include a debate on ownership and creation of art (Fisher, 2023). However, as was mentioned, there are still some issues, which can be seen as rather questionable, such as the influence of the described bias in generated data and ethical questions connected with cognitive work on AI (Dwivedi et al., 2021).

OSCM is increasingly adopting advanced technologies to enhance efficiency and competitiveness. One such technology, Generative Artificial Intelligence (GenAI), is poised to revolutionize SCM by offering capabilities beyond traditional AI approaches. GenAI, a subset of AI that focuses on creating original material based on learning from real-world data, has the potential to transform SCM processes by optimizing decision-making, improving operational workflows, and achieving unprecedented levels of productivity.

The significance of GenAI in SCM lies in its ability to analyze vast amounts of data, identify patterns, and generate valuable insights. Unlike traditional AI, which is often limited to specific tasks, GenAI's capacity to create new content, such as written text, images, music, and simulations, opens up a wide range of possibilities for enhancing SCM operations. By leveraging GenAI, organizations can automate tasks, predict future trends, and adapt to dynamic market conditions with greater agility.

Furthermore, GenAI's role in SCM extends beyond operational efficiency. It also plays a crucial role in strategic decision-making, such as inventory management, demand forecasting, logistics optimization, and supplier selection. By harnessing the power of GenAI, supply chain professionals can make informed decisions, reduce costs, and improve customer satisfaction.

Therefore, with the help of Gen-AI technology, firstly, supply chain experts got effective tools that can enhance the priority domains of SCM, such as inventory (Benmamoun et al., 2018) and demand management, optimization of logistics (Benmamoun et al., 2023), supplier evaluation, and supplier risk management. Hence, Gen-AI algorithms can be effectively used for analysis the of past data, identifying patterns, and using them to forecast future demand for products and services to help reduce inventories, minimize out-of-stock situations, and maintain a low carrying cost. The second example of application of the Gen-AI-powered systems concerns improvements of the organizational and communication parameters of logistic and transportation systems with consequent increases in its cost-effectiveness and positive impact on the environment including storage and the choice of optimal routes and fuel consumption.

AI has emerged as a cornerstone of Industry 5.0, extending its influence beyond the shop floor into diverse areas such as predictive maintenance, human-robot collaboration, and supply chain adaptation (Rane, 2023a; Schmittner and Abdelkader Magdy, 2023).

In light of these advancements, understanding the background and implications of GenAI in SCM is crucial for organizations seeking to stay competitive in the rapidly evolving business landscape. This paper aims to explore the current opportunities and challenges of implementing GenAI in SCM, shedding light on its transformative potential and paving the way for future research and innovation in the field.

The literature shows an exponential growth of research in GenAI in the industry and particularly in Supply chains. This growth underscores the significance and relevance of GenAI in contemporary research and innovation. However, there is still a gap between research and GenAI applications in the real world. With this background, in this study we seek to answer the two major research questions: (1) What are the current opportunities and potential applications of Gen AI in Supply Chain Management? and (2) what are the overall challenges related to GenAI technologies implementation in the context of Supply Chain Management? The remainder of this paper is arranged as follows: Section 2 summarizes our methodology. Section 3 describes the opportunities and applications of GenAI in the SCM field. Section 4 examines the key challenges and limitations of GenAI implementation in SCM from technical limitations to industry challenges. Finally, Section 5 concludes by spotlighting this study's significant findings.

2. Methodology

To develop this article, literature was based on reading several academic articles on the topic, especially Scopus articles, as well as research on the subject. It appears that the topic is already widely studied, which further reinforces its relevance.

The historical chronology shows an increase in articles, especially in 2023, and **Figure 1** visualizes the growth in the volume of papers concerning this topic during this period. **Figure 2** illustrates the increase in Articles and conferences in this area. This tendency, which will increase quickly in 2022 and 2023, is consistent via the introduction of advanced Gen-AI systems like ChatGPT. The findings of this research demonstrate how Gen-AI might increase management efficiency has been recognized, which has raised awareness of the advantages of incorporating Gen-AI into organizational structures and operations between managers, company executives, and government organizations.

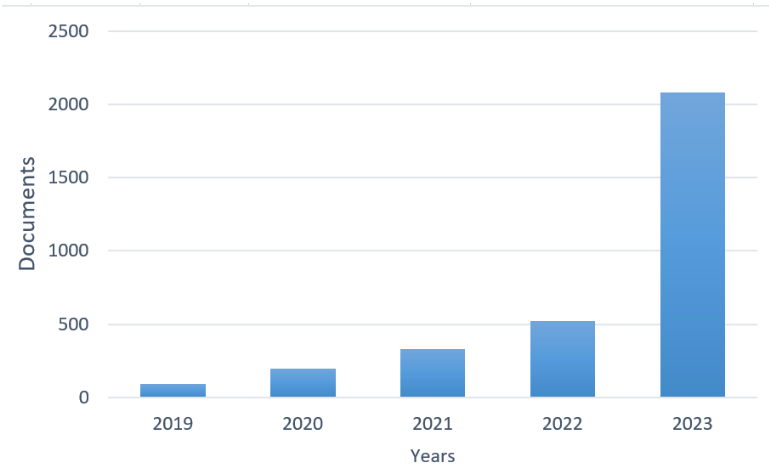

Figure 1. The number of research papers and publications about the application of Gen-AI (2019–2023).

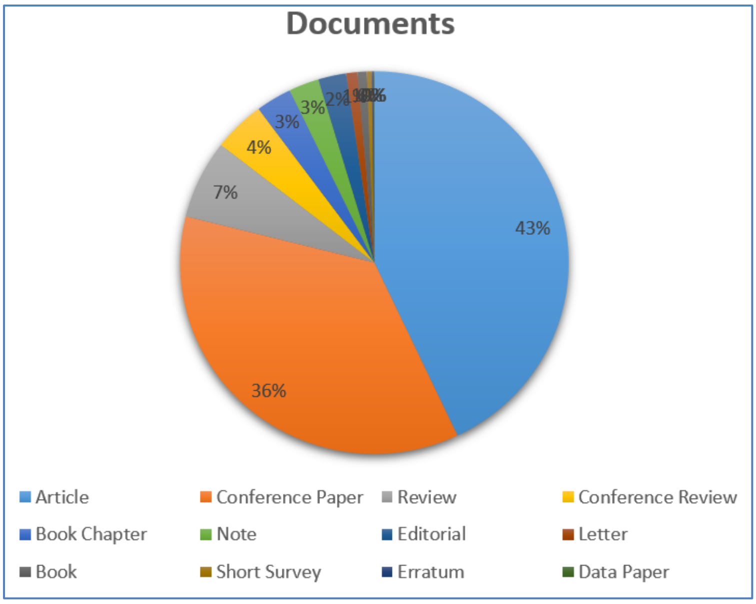

Figure 2. The articles by type regarding the use of Gen-AI (2019–2023).

SCM is a system of interconnected operations that generates raw materials, converts them into intermediate and finished goods, and then uses a distribution network to deliver them to consumers.

Gen-AI implementation in supply chains is increasingly intimately linked to business innovation. It involves integrating new technology and drastically altering operational standards. AI's ability to analyze huge quantities of data, generate insightful conclusions, and facilitate individual decision-making has encouraged improvement in SCM (Kumar et al., 2019). First, the use of Gen-AI fosters innovation by improving operational efficiency (Benmamoun et al., 2018; Benmamoun et al., 2023; Dwivedi et al., 2021; Fisher, 2023; Rane, 2023b; Schmittner and Abdelkader Magdy, 2023; Wael AL-khatib,2023). Machine learning algorithms provide organizations with precise information on supplier behavior, demand patterns, and logistical intricacies.

3. Applications of Gen AI in SCM

3.1. Supply chain management

Supply Chain Management represents the concept of scheduling and carrying out all sourcing and procurement-related operations, and transformation. The CSCMP "Council of Supply Chain Management Professionals" was the first logistics organization that provided "all logistics management activities" in 1963. Coordination and cooperation with channel partners, suppliers, retailers, outside suppliers of services, and clients are also included. Supply and demand management are integrated both inside and across businesses through SCM (Akbari and Do, 2021). The procurement of raw materials is the first step in the SCM process. The raw material is gathered by the product manufacturer's supplier. The producers supply the final goods after refining the raw material. Wholesalers handle the product distribution process once the product is manufactured. Retailers purchase these things from wholesalers, while customers often purchase goods from retailers. **Figure 3** shows the SCM technique's overall diagram.

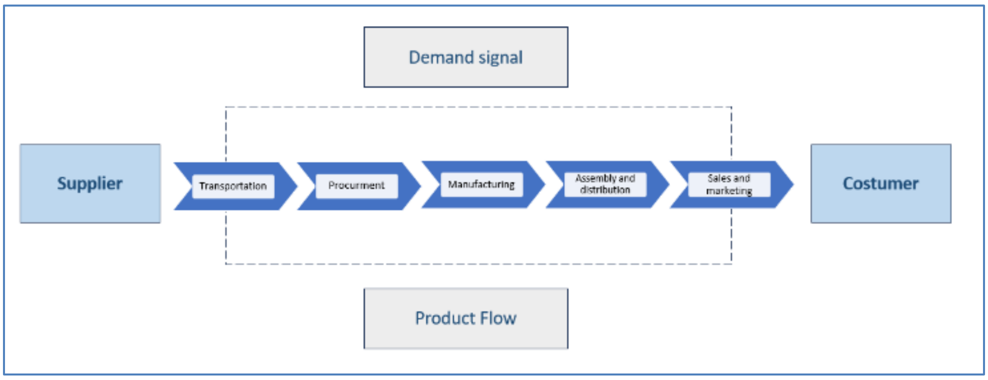

Figure 3. General SCM.

Successful businesses have developed a clear and concentrated concept of creating value, regardless of whether it is associated with luxury goods, specially designed services, or generic, low-cost merchandise. regardless of how effective your marketing is, though, if the item or service cannot be provided to the customer at a reasonable price, nobody will purchase it. Since many items sit in stockpiles for six months to a year or longer, many businesses need to enhance their SCM. Because the items are kept in inventory for extended periods, there is a great chance to improve delivery, lower expenses, shorten cycle times, and boost flexibility—all of which will contribute to a further decrease in inventories. Numerous businesses have enhanced their supply chain through internal processes. They understand that it relates to outside customers as well as suppliers, and by doing so, they may enhance their operations even more. SCM, according to Krichen and Ben (2015), is the process of making decisions that coordinate many operations to provide profitable outcomes for vendors, retailers, and consumers. Production, sourcing, developing goods, logistical responses, and every stream that connects these activities may all be made more economically by effectively arranging the various operations. It could also be a procedure that maximizes a group of choices. This process produces effective answers that offer effective strategies for operating on several levels and taking into account all points of view while making decisions. Whatever your major, learning about OSCM is essential, according to Krichen and Ben (2015) and Jacobs and Richard (2018). They said that regardless of your interest in finance, development all values to the chosen currency. Once you do, you'll realize that currency is all about transporting, storing, and exchanging value. In the modern world, SCM is essential. Gour Chandra et al. give a formal definition of a supply chain so that the reader can understand what this concept is. A collection of individuals and connections are referred to as supply networks. The terms "upstream" and "downstream" refer to the material and information flows in this supply network. The client is located downstream, and the initial provider is located upstream (Mahata et al., 2023).

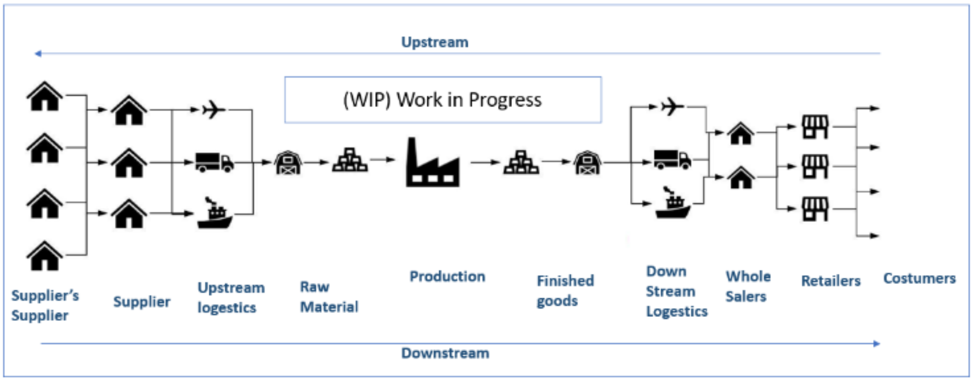

Figure 4. Supply chain overview.

SCM is essential to modern corporate operations, as seen in **Figure 4**. Materials and necessary data, such as usage standards, invoices, stock levels, etc., are sent downstream from the supplier to the client and continue until the materials are converted into the finished item and sold to the final consumer. Merchandise that a customer returns to the original supplier, such as faulty units, customer returns, recyclables, etc., are found upstream (Mahata et al., 2023), together with necessary data such as demand forecasts and predictions. Suppliers can more easily plan capacity and inventory levels. when they have access to forecasts and demand data (Pournader et al., 2021).

3.2. AI to Generative AI

Artificial intelligence is a blanket term that includes many computing algorithms that can execute activities that are normally associated with human intellect, such as comprehending natural language, identifying trends, arriving at judgments, and gaining experience (Castelvecchi, 2016; Winston, 1984). Expert platforms with knowledge bases were examples of first-generation AI technologies that were rules-based and intended to assist users and enterprises in making decisions (Harmon and King, 1985; Patterson, 1990). One area of AI called machine learning (ML) is concerned with creating algorithms that don't require explicit programming and are capable of solving problems on their own by learning from data

(Brynjolfsson and Mitchell, 2017). In **Figure 5**, Banh and Strobel (2023) distinguish differing from previous AI concepts, Gen-AI provides an important conception.

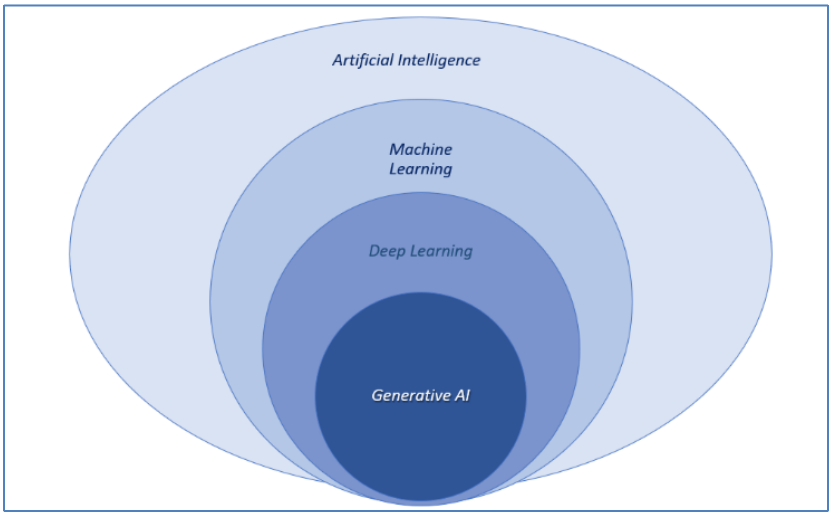

Figure 5. Gen-AI and other AI approaches (Goodfellow et al., 2016).

According to the type of data and the intended result, ML includes a variety of learning methodologies. Supervised learning is a popular method used in commercial settings, through which algorithms are created to anticipate or classify (businesses) data using identified datasets (Janiesch et al., 2021), the technique of identifying hidden structures or patterns in unlabeled data is known as unsupervised learning (Kühl et al., 2022), as well as learning through reinforcement is the application of additional machine learning strategies.

Precisely, Deep Learning (DL) is a subset of ML and defines an area of machine learning where artificial neural networks are used. These ones are modeled after the human brain and hence can learn from big data sets (Janiesch et al., 2021). The ability of DL to directly learn representations from massive data is especially beneficial for such applications as image- and speech-recognition, natural language processing, and so on (Kühl et al., 2022). In DL models, there are various layers of nodes interconnected through which features are hierarchically extracted from the input (Janiesch et al., 2021; Kühl et al., 2022; Samtani et al., 2023). As far as the demand estimation is concerned in particular, the DL models can integrate past demand along with environmental factors, factors such as economic conditions, weather, and marketing campaigns to estimate future demand accurately. This is made possible through the model capacity to easily detect interactions and interdependencies that may not easily be discerned by such methods (Kumar et al., 2020). In pricing optimization, while creating DL models they have the capacity to figure out many factors like past sales data, competitors price, common trends, and customer categories to change the price same time. This makes it possible for the companies to record high levels of revenues as well as decent levels of profit regardless of the costs of production, besides satisfying the market needs. Since DL has the ability to analyze and comprehend large amounts of information, it is used to help businesses make the right price decisions at the right time while responding to the ever-changing market forces and customers' behaviors (Li et al., 2023; Li et al., 2023; Zhang et al., 2023).

Altogether, the ability of DL to learn and self-adapt depending on the data nature makes this tool useful in several fields and cases, including demand estimation, genuine and fake reviews, the best pricing strategy, and so on.

Gen-AI is useful in many different contexts, such as creating text, images, videos, code, sounds, and other created stuff like molecules or three-dimensional representations. Recently, discriminative Gen-AI complementing has become a fresh instrument with a plethora of new possibilities affecting several industries, from networked enterprises (Brand et al., 2023; Burger et al., 2023) to education and healthcare (Cooper, 2023; Dwivedi et al., 2023a; Wessel et al., 2023). Beyond merely providing support, these new applications can generate original and innovative material since they acquire the characteristics of Gen-AI related to generativity and variance. As a result, Gen-AI is becoming more interdisciplinary, which makes allowances for innovative technological advances and automates even traditionally creative work, such as developing personalized illustrative texts or images. This opens up new chances for companies to set themselves apart in the competitive world of business (Brand et al., 2023; Burger et al., 2023; Lund et al., 2023).

Using a classification based on architectural features, Bandi et al. investigate the different Gen-AI model types identified in the literature. These include language models, transformers, diffusion models, variational autoencoders (VAEs), normalizing flow models, generative adversarial networks (GANs), and hybrid ones. There is also an extensive categorization of the input and output formats that are utilized by Gen-AI systems. Additionally, the study explores widely used assessment metrics in Gen-AI and suggests a categorization scheme based on output kinds. Researchers, developers, and practitioners may use the findings to efficiently construct and assess Gen-AI models for a range of applications, leading to improvements in the area. The importance of the study comes from realizing that optimal performance and efficient planning and design of Gen-AI systems depend on certain prerequisites (Bandi et al., 2023).

3.3. Generative AI applications in SCM

Indeed, across industries including healthcare (Dhudasia et al., 2021; Khlie and Abouabdellah, 2017a; Li et al., 2023), education (Baidoo-Anu and Owusu Ansah, 2023; Bahrini et al., 2023; Nikolic et al., 2023), information systems (Dwivedi et al., 2023b), and hospitality and tourism (Bandi et al., 2023; Dogru et al., 2023; Dwivedi et al., 2023b; Khlie and Abouabdellah, 2017a), the body of research on Gen-AI is expanding at a rapid pace. Nonetheless, OSCM is still in the early stages as far as the corresponding sectors are concerned (Hendriksen, 2023; Kumar et al., 2023)

Regarding this, real-world retail case studies were examined by Kumar et al. (Kumar et al., 2023), who also presented a trade-off regarding ChatGPT's ability to provide round-the-clock customer care. However, in terms of personalized suggestions, the tool's incapacity to identify uncommon languages may leave users unhappy.

Hendriksen emphasizes that human comprehension and interpretation are necessary for integrating Gen-AI in OSCM from an overall viewpoint (Hendriksen, 2023). The lack of theoretical aspects of OSCM viewpoints for comprehending the interaction between technology and people and how to potentialize outcomes while reducing risks is another concern brought up. This claim can be supported by the fact that most papers address Gen-AI in OSCM.

Utilization of Gen-AI in OSCM reporting offers significant advantages from an operational standpoint. Through the application of Gen-AI to automate repetitive operations, such as management of inventory, purchase orders, invoices, as well as shipment, organizations may enhance their decision-making processes (Ashcroft, 2023; Murris, 2023).

The grey literature raises some of the same issues with including Gen-AI as does the emerging academic research on the subject. For example, how the user submits the queries, how consistently and reliably the system is fed, and how sensitive information is handled are all factors that affect how well Gen-AI and ChatGPT respond (Pukkila, 2023; Stancati and Schechner, 2023). Within the supply chain and logistics domains, obtaining precise and pertinent Information generated by Gen-AI/ChatGPT appears to have become a significant challenge.

Regarding the integration of machines and humans, or extra precisely, the Gen-AI human connection, the present focus of Gen-AI/ChatGPT, is today's focus of Gen-AI. According to Ritala et al. (2023) worker and organizational knowledge may coexist happily by a well-defined limit concerning repeated activities, alternatively, human beings should engage in imaginative activities (perhaps via assistance from ChatGPT/Gen-AI) (Fui-Hoon Nah, 2023; Ritala et al., 2023).

Figure 6. Gen-AI in OSCM.

The conventional methods of sourcing analysis and procurement are revolutionized by the application of Gen-AI in SCM. In contrast to human analysis and decision-making processes, Generative AI offers a sophisticated mechanism that quickly sorts through large amounts of data from several possible sources (Lal et al., 2018). It also helps in creating a variety of contractual conditions and negotiating strategies based on past performance and projected supplier behavior (Richey et al., 2023).

The most common application of Gen-AI in OSCM is seen in **Figure 6**. Gen-AI is widely used in supply chain risk reduction, offering a variety of tools and features that revolutionize the way potential disruptions are handled. This technology can analyze massive amounts of data, both historical and present, by using complex algorithms. According to He et al. (2020), the primary application of Gen-AI for risk mitigation is projected risk analysis. Gen-AI systems look at historical data, current patterns, and outside variables to forecast potential disruptions. If supply chain managers possess this sort of future knowledge, they may plan strategies and take generative AI can also be beneficial to supply chain operations (Spaniol and Rowland, 2023). Using both historical and current data, this program creates a variety of risk scenarios that aid in assessing potential outcomes and creating precise backup plans for various risk kinds. These simulations are a crucial tool for assessing the effectiveness of mitigation strategies.

Additionally, Gen-AI-driven models that create alternative supply chains, find replacement suppliers, and employ different procurement techniques provide the supply chain with the strongest protection versus weaknesses, maximizing its resilience. This proactive strategy guarantees that operations continue even in the event of interruptions by lowering dependency on particular nodes within the chain. Gen-AI is used in risk management (partner, political, economic, and cultural risks), where models are produced of potential disruptions for risk assessment based on scenarios that include occurrences like catastrophes, epidemics, supplier insolvency, and more.

Gen-AI has enormous promise for effectively coordinating supply chain logistics, transportation, and distribution (Kalasani, 2023). When it comes to handling a range of objectives and constraints, this technology excels at developing intricate plans that are ideal for optimizing logistics and distribution routes (**Figure 6**, the most utilized of Gen-AI in Supply chain and operations). These include reducing expenses, maximizing service levels, reducing disruptions in route, accounting for weather, and integrating environmental considerations. Moreover, Gen-AI is adept at developing contingency plans to mitigate disruptions like traffic congestion and extreme weather. By analyzing a range of real-time factors, such as weather predictions, vehicle specifications, traffic patterns, and fuel costs, transportation routes with optimal efficiency are automatically generated using Gen-AI algorithms (Saheb et al., 2022). For instance, by carefully planning a delivery truck route in an urban area, the Gen-AI system may save fuel consumption and travel time while allowing for many stops.

Gen-AI's predictive capabilities improve procurement and improve the precision of inventory, making significant changes to supply chain processes related to demand forecasting and inventory management (Meriton et al., 2020; Syntetos et al., 2016). The most optimal scheduling of supplier quantities and orders is made possible by the very accurate sales and demand estimates that companies can deliver thanks to their predictive skills. Lean management approaches, which significantly reduce waste and boost process and resource efficiency, are made simpler to implement by using GenAI (Cao et al., 2019; Jebbor et al., 2023; Khlie and

Abouabdellah, 2017b; Myers and Berry, 1999; Syntetos et al., 2016). In addition, GenAI was also used in automating Workflow, optimizing layouts (Rane, 2023a), streamlining tasks, and minimizing lean waste (Filippi, 2023; Votto et al., 2021). GenAI also plays a crucial role in production scheduling, cost estimation, resource allocation, and production schedule optimization by simulating multiple assembly line configurations to define the most efficient set ups before implementing it into the real world. Furthermore, it helps speed up the industry evolution by generating modeling trends, patterns and relationships in Data, this allows to come up with new ideas or solutions that can help develop new products, explore new design specifications, identify potential gaps or suggest new combinations or features (Jebbor et al., 2024).

Generative AI can also enhance safety and risk management (Mani et al., 2017) by providing an accurate risk estimation and generating specific risk measures (Garvey et al., 2015). It is considered a powerful tool for identifying risks and detecting errors or deficiencies even before they occur (Rane, 2023b).

GenAI was also used to enhance the sustainability level of the company by ensuring a sustainable/green supplier selection and evaluation (Govindan et al., 2015). Generative AI brings a large number of opportunities to all types of industries (Ufuk, 2023) but has several limitations that need to be addressed (King, 2023).

Suppliers, inventories, and customers' data must be managed and analyzed by using artificial intelligence for the manufacturing industry. For example, in supply chain, current data from different suppliers can be used to determine algorithms to inform on the time taken in delivering the goods to those suppliers so that stocks do not run out. Of course, it can lead to decrease of lead times and increase of level of satisfied customers. Moreover, AI for supply chain in manufacturing industries can enable them to benchmark different opportunities to improve the last mile delivery, easy determination of routing, real-time control of the drivers' performance in supply chain that can be calculated not only in histories but also in the weather and traffic outlook in order to improve efficiency and effectiveness in estimating the future delivery time. McKinsey also affirms that AI is also expected to newly add value in improving supply chain since it's likely to reduce the forecasting errors by 20%–50%, lost sales by 65%, and over-stocked inventory by 20%–50% (Mohan Mewari and Kamath, 2021). For instance, BMW has lately introduced an AI, advanced supply chain management system dependent on machine learning techniques that analyses data regarding suppliers and the consumers as well as inventory and demand (Diianni and De Girloamo, 2021). With the help of the system, such factor as the overall costs of inventory has been almost eliminated along with improving the punctuality of the car deliveries. An example is the car manufacturing company called Rolls Royce where they integrate self-driving floats that are driven through machine deep learning algorithms and image recognition, to ensure supply chain satisfaction and safely transport it goods (Mohan Mewari and Kamath, 2021). There is a tremendous opportunity to use generative AI to manage logistics, transportation, and distribution of products in supply networks (Kalasani, 2023). When used in generating speeches this technology is most applicable in generating highly intricate plans that fit logistical and distribution objectives and constraints in addition to other objectives and constraints. Some of the ones described include reducing the cost, increasing the service levels, avoiding the interruption of several routes, working the weather, and integrating the environment into the kind of solution reached. The application of generative AI creates a drastic change in demand forecasting and inventory management functions of supply chains reduce procurement distortions and enhances the precision of inventories (Meriton et al., 2020). One primary advantage of demand forecasting is that it means that firms are in a position to be able to give near-perfect forecasts on sales and demand that enable the firm to schedule the quantity and orders from the supplier in the most optimal manner.

4. Challenges and limitations of Gen AI in SCM

Several GenAI challenges were discussed in the literature. We have classified them into Four areas as shown in **Figure 7**.

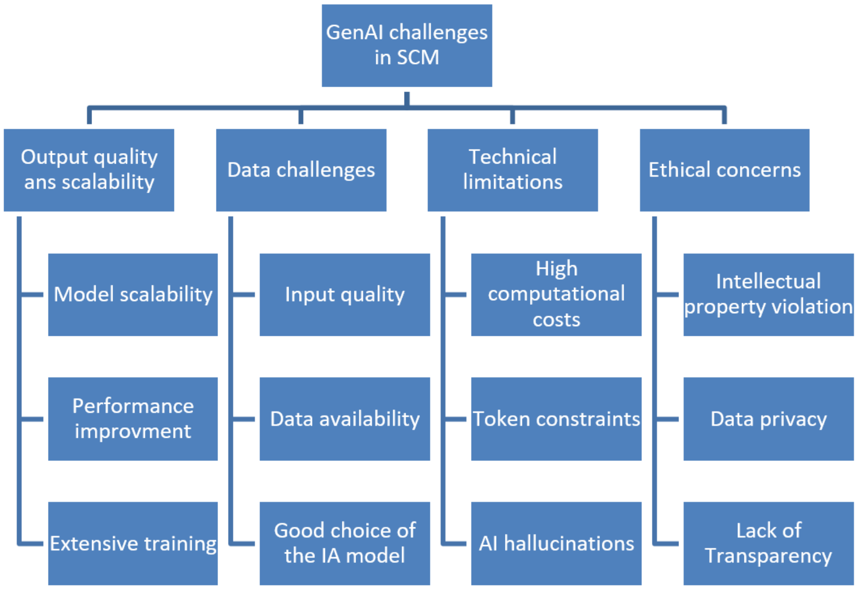

Figure 7. GenAI Challenges in SCM.

4.1. Output quality and scalability

Maintaining quality outputs while ensuring scalability to accommodate the growing business demands remains a complex challenge. As the business evolves, AI systems should ideally grow and adapt seamlessly. However, achieving this scalability without compromising output quality is a delicate balance that organizations strive to maintain.

In addition, improving the GenAI model performance over time can be challenging because AI models are black box and it can be difficult to understand why they generate a given output which makes it difficult to improve. Moreover, to ensure an optimal utilization of GenAI systems, it is required to offer extensive and continuous training to the employees. This requires a significant amount of time and money.

Generative AI models are limited by the data they are trained on, for long-term effectiveness as they might not be able to keep up with the fast-changing contexts or environments.

4.2. Data challenges

The integration of Gen AI into SCM introduces various challenges related to data quality and availability. This section highlights the potential pitfalls of errors in input data and emphasizes the critical need for rigorous data quality control. Additionally, it discusses the frequency of data refresh and the challenge of assimilating a vast amount of data in different formats to ensure accurate predictions for products and markets.

One of the biggest challenges in Data collection is to ensure its accuracy. Errors in input data can easily lead the company into the wrong path.

In addition, Each AI system generates a specific format of data and requires a specific frequency of data refresh. it is required to choose the right AI system depending on the data availability and frequency of updates. Data might need to refreshed daily, weekly or monthly and in some cases, a continuous stream of real-time data might even be needed. For demand forecasting, updating the data frequently to include past sales performance, economic indicators, reports on industry trends and customer behavior would be a challenge.

4.3. Technical limitations

Gen AI encounters several technical challenges that impact its effectiveness. High computational costs, Token constraints, and AI hallucinations.

AI hallucinations occur when the algorithm is trying to overfit on a small or biased set of data, which results in generating outputs that are not representative of the real world. In the following sections, we present examples of key applications of generative AI, and challenges created by generative AI (Kalasani, 2023). AI hallucinations are outlined as notable issues that organizations must grapple with to ensure the smooth functioning of Generative AI models.

Generating new content can require significant computing space, power, and time. With limited graphic processing units, called tokens, can limit the format of data used for training the AI model and limit the system's ability to handle large data sets or generate results quickly.

The AI system should be able to assimilate a large amount of data in different formats and continuously update as new data becomes available and finally generate accurate predictions for products and markets.

4.4. Ethical concerns

Security, transparency, intellectual property violations, and privacy concerns emerge as critical ethical considerations in the application of GenAI in SCM. This section delves into the multifaceted ethical challenges organizations face, such as protecting sensitive company data, ensuring transparency in algorithmic decisions, and mitigating the risk of intellectual property violations. Due to concerns about privacy and information security, a growing number of ChatGPT bans or restrictions have been imposed by organizations and countries (Meriton et al., 2020).

When a company is using AI systems, one important thing to do is to ensure that the company is not infringing unintentionally on any copyrights or trademarks. Compliance with copyright and trademark laws is very important to avoid violations.

The opaqueness of GenAI models poses a significant challenge in understanding how the model works or how decisions are made. This lack of transparency makes it difficult to understand the decision-making process.

Another challenge related to Data is Privacy. Protecting sensitive company data should be a top priority- companies need to be careful about how they collect, how they store and how they use data- implement best practices to ensure data remains secure and confidential), transparency (disclosing the type of data used in their algorithms or explaining the decisions made by the system), have clear policies to safeguard sensitive data that complies with local lows. Educate employees on how to handle data responsibly.

With AI challenges, it is important to keep AI principles in mind. Not having a good understanding of AI. We cannot lead what we can't understand. Having a collective understanding of AI is crucial for the team to overcome any hesitations or fears and to be able to make informed decisions moving forward.

5. Discussion

It is worth stating that the use of GenAI in SCM has been quite productive; however, being able to unlock its potential also brings key challenges into the spotlight. It will also provide a discussion of these aspects based on the analysis made in the study's previous sections.

5.1. Opportunities of GenAI in SCM

Chances are found in SCM where GenAI may impact positively on change, development, and advancement. One more advantage of GenAI in different fields of SCM is its ability to work with large datasets, recognize numbers and patterns, and generate new materials. For instance, applications like inventorying and demand estimation might be profoundly improved by such elements of predictabilities from this GenAI. Demand forecasting allows for accurate projection by firms hence avoiding cases of over stocking, and stock out resulting in low carrying costs which in turn enhances firm operations.

Besides, GenAI can enhance the current logistics and transportation of the products and services by identifying the right and optimal channels and also by reducing the fuel consumption rate and carbon emission. It not only increases the probability of outcompeting rivals and obtaining better financial returns but also complies with programs of the environment of the world.

In addition, GenAI can also be useful to assist in the assessment and mitigation of risk concerning suppliers by providing a full explanation of a supplier's capacity to supply value-added products and services and an evaluation of the probability of disruption of relations.

The implementation of strategic decision-making cannot be overemphasized in GenAI and decision-making related to GenAI. It may concern demand forecast to logistics or any other part of the supply chain it is great to be able to decide based on all the available data. This helps supply chain managers to move up the chain and focus on more complex tasks and come up with valuable and meaningful outputs at the same time thus improving the overall process and decisions made.

5.2. Challenges and ethical considerations

However, this paper has identified the following challenges likely to hamper the implementation of GenAI in SCM; Some of the big issues that can be found in the context of big data are Data quality and Data reliability. Computational algorithms in the form of GenAI systems depend on data used in their development, and any misinformation on the data sets leads to a poor result. The quality of the collected data is highly important to optimize GenAI following the principles of high-quality recommendations and services.

The novelty, however, brings a major issue when utilizing GenAI; it entails ethical practice. The possible bias in the generated data, the job loss effect, and other consequential effects in other decision-making processes need to be controlled. Transparency and interpretability of GenAI systems to build trust and make sure that the decisions made by GenAI systems would be as ethical as possible.

However, the technological implementation of GenAI into the current SCM systems is a technical issue. It is a known fact that integration of new GenAI technologies with the old traditional systems would be an issue, followed by the importance of investing heavily in relevant infrastructure and training, as well as likely resistance by isomorphic forces within organizations.

6. Conclusion

In conclusion, the integration of Generative AI in Supply Chain Management represents a paradigm shift, offering promising advancements and applications that redefine industry standards. The paper has provided an in-depth exploration of GenAI's exponential growth in scientific research, its transformative applications in SCM, and the intricate challenges and limitations encountered in its implementation.

The insights derived from this study serve as a valuable resource for practitioners, researchers, and policymakers navigating the evolving landscape of Generative AI in the context of Industry 5.0. As GenAI continues to shape the future of SCM, addressing the outlined challenges becomes imperative to ensure not only the ethical but also the effective implementation of this powerful technology. This study contributes to the collective understanding of the intricate interplay between Generative AI and Supply Chain Management, paving the way for informed decisions and strategic advancements in the field.

Therefore, future studies should address the following areas in utilizing GenAI to its optimum level in SCM. Firstly, it is crucial to work on the methods that would primarily define the quality and fairness of data utilized in GenAI systems. Substantial work will be necessary to develop new data cleaning and preprocessing methods and to find impartiality in data.

Second, there is the issue of ethical consideration that should be addressed with regard to GenAI. It is essential to set a standard as to how GenAI is to be used ethically in SCM to minimize the confusion with the principles of AI ethics. Some of these are issues concerning job loss, explanation, and responsibility.

Finally, Generation AI has a revolutionary impact on Supply Chain Management carrying the potential to perform many functions with high efficiency and provide better and wiser decisions in the future. Nevertheless, achieving this vision is possible, while threatening to be hampered by multiple relevant issues regarding the quality, ethics, and integration of data. Subsequent works & practical endeavors need to dedicate attention to these domains to provide the inclusion of GenAI into SCM, as well as to develop its optimal application to avoid risks & at the same time, achieve maximum effectiveness.

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