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Exploring Data-Driven Decision-Making for Enhanced Sustainability

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Abstract. The industry transition towards digital transformation opens the possibilities to utilize data for enhancing sustainability in industrial operations and build capabilities towards resilient and circular operations, i.e., shift towards industry 5.0. This paper explores how data-driven decision-making (DDDM) can enable sustainable and resilient supply chain operations within the manufacturing industry. A series of in-depth interviews were conducted with experts, researchers, and company representatives across the manufacturing industry and universities in Sweden. The findings show a consensus among companies, researchers, and literature about the potential of data utilization for sustainability purposes; however, in most cases, the complete transformation towards data-driven has not happened yet. Companies have uncertainty about what data is needed rather than its lack. Reliability & validity of data become essential to exploit the potential of the data organizations already possess. Based on the literature and interview data, a conceptual model is proposed, including three identified parameters connected to DDDM, 1) data and IT infrastructure, 2) current operations, and 3) an improved triple bottom line performance. The model captures the interconnections between such parameters, depicting the benefits and challenges of DDDM and its relation to more sustainable and resilient supply chain operations within the manufacturing industry. In a data-driven approach, real-time analysis of complex & extensive amounts of data gives unlimited possibilities to improve manufacturing operations through decision-making.

Keywords. Data-driven, decision-making, sustainable manufacturing, digitalization, sustainability

1. Introduction

Digitalized manufacturing enables flexible and cost-efficient production systems, including autonomous production, connected business entities, and integrated business systems [1]. Adopting digital technologies has successfully met industrial challenges such as the higher demand for customization, flexibility, and productivity [2].

The sustainability approach is a process by which companies integrate their economic, social and environmental objectives into their business strategies and optimize the balance among all three [3]. Digitalization can be utilized to the extent to not only benefit companies' economic progress but also to improve the sustainability aspects of their operations [4]. It can significantly enhance resource usage, leading towards a more sustainable production system with Triple Bottom Line (TBL) benefits, e.g., economic,

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social, and environmental. Generally, manufacturing losses are often linked with breakdowns and rippling effects, i.e., idle or blocked machine states [5]. To overcome these types of losses, a solution is to utilize Decision Support Systems [6,7]. For example, machine operation and maintenance can cause bottlenecks in the production system, which are usually difficult to anticipate [8]. Data-driven decision-making (DDDM) refers to the process of making decisions based on the analysis of data rather than on intuition [9]. Companies improve bottlenecks' prediction through decision support systems, meaning they can make decisions based on data analysis for better production and maintenance planning.

As the need for a digital transformation within society and businesses increases, the challenge of digital integration is intensifying. Manufacturing companies can often collect large amounts of data but often fail to capitalize on the benefits of the data in their digital applications. A large number of digital transformations fail to improve performance because of implementation challenges [10]. Even if a company has the right approach to implement a digital foundation, additional factors such as environmental regulations and external circumstances can also inhibit digital integration. Still today, the productivity of such investments is questioned, as organizations' skills are lagging behind when it comes to technology advancements [11]. Therefore, there is a need to understand how manufacturers can utilize data appropriately to make faster and better decisions and ultimately improve their sustainable performance. In addition, it is essential to identify the underlying reasons why digitized systems sometimes fail to deliver desired results, especially as the outburst of Covid-19 has changed the business landscape drastically. Thus, this study aims to explore the benefits and challenges of DDDM and its relation to sustainable supply chain operations in the Manufacturing Industry. The present study sees DDDM at a general level; therefore, technical aspects such as specific algorithms that make automated decisions are excluded. Instead, the focus is on the holistic meaning of the concept and how it impacts companies' manufacturing operations. The focus is on what DDDM entails regarding business activities, digitization, performance, and sustainability.

2. Theoretical background

2.1 Data-driven decision making in the manufacturing industry

Data is nowadays seen as a key resource for an organization, with endless potential [12]. Service and manufacturing supply chain management have been integrating digitalization for an extended time [13]. Supply chain management and Big Data capabilities enable better decision-making systems, providing faster responsiveness to disruptions and failures [13,14]. In literature [15], two different types of decisions are illustrated: decisions connected to 'discoveries' and decisions that underline and strengthen an initiative-based decision. Data could, for instance, supply more knowledge to a given situation to facilitate better forecasting, in which discoveries can be recognized. It is further argued that data-driven firms are more productive and that the productivity increases the more data-driven a firm is [11]. Thus, DDDM facilitates the solution for complex business problems.

The main difficulties for DDDM are usually compiled using the 5Vs, which stand for Volume, Velocity, Variety, Verification, and Value [13]. For instance, a manufacturer generates approximately 4 trillion data samples per year, i.e., volume challenge [16]. Velocity is the challenge of efficient data management, where the reliability of data transfer and data collection is fundamental. Furthermore, data sources such as sensors can come in multiple formats, which leads to the challenge of variety and integrating diverse sets of data into a standard format. In addition, much of the available data is not always sufficient to make complex decisions, leading to the challenge of verifying the data from good to bad. Lastly, it is not always straightforward if the value of data is satisfying, as it is difficult to measure the overall impact that it can create [13].

Looking at the supply chain level, organizations are in a dire situation to develop digitalization strategies as it is one of the fundamental parts of businesses [17]. With a digitalized supply chain, numerous opportunities can be achieved, such as increased information availability, transparency, access and control, and operations efficiency [18]. For instance, by having data on time of order, time of arrival, lead time, cost price, and the number of units ordered, supply chain operations can be optimized with the help of DDDM [19]. It becomes essential to understand data-driven manufacturing and how to enable it, especially what type of manufacturing data a company collects, how it connects to manufacturing and supply chain, and the obstacles to an optimized data-driven supply chain.

2.2 The triple bottom line of sustainability in manufacturing

In compliance with the sustainable development goals (SDGs), industries are urged to act to meet the global goals demanded by society with a deadline in 2030. Digital technologies in the manufacturing industry continue evolving, showing multiple benefits, such as end-to-end transparency, agility, connectivity, resource optimization, and holistic decision making [20]. Today, the industry needs to re-think the purpose of technologies, connecting the benefits to an improved organizational performance that includes the TBL [21]. Building sustainability is about long-term strategies and the result of long-term stability, which can be built with the support of digital technologies.

The internal performance is often interconnected with the economic aspect, whereas the external performance is linked with the environmental and social aspects [21]. Process efficiency built by technologies can be connected to a positive impact on the environment, as the usage of resources, e.g., raw materials, human labour, etc., can be optimized, and process waste reduced. Additionally, sensors and tracking technologies could further improve waste management, thus reducing the environmental footprint. Previous research studies [22,23] show the benefits and risks of Industry 4.0 and emerging technologies required for a digital supply network. The benefits are enhanced efficiency, flexibility, customization, quality, transparency of green-house emissions, fair wages, human learning, and employee motivation.

The exchange of data is one of the weakest features concerning data privacy [23]. It carries risks such as cyber-crime, unauthorised information access, and industrial spying [22]. Business processes also utilize substantial energy that negatively impacts the environment [4]. It is necessary to develop a further understanding of sustainable risks specific to emerging applications within digitalization.

2.3 Data-driven decision-making as an enabler for sustainable operations

The technologies development provides enormous opportunities for realizing sustainable manufacturing via information and communication technology infrastructure [24]. In pursuing a significant organizational digital transformation, the management must consider several aspects of successful transformation, including economic and social sustainability considerations [25]. By adopting sustainability principles, businesses can become more profitable and sustain their activities over the long term. Digitalization, specifically DDDM, can be utilized beyond companies' economic progress, i.e., to improve social and environmental aspects of their operations [4,26]. For instance, industries can adopt green strategies for logistics activities to minimize logistics operations' costs and waste [20]. A digital supply network allows for a more sustainable strategy for transport, warehousing, office management, inventory control, and material handling systems, which all help achieve sustainable logistics systems [21].

Manufacturing companies strive to reduce the energy consumption for machinery operations to minimize waste and raw materials used in production processes [6,20]. Less focus has been observed regarding social sustainability than economic and environmental aspects; however, the end goal to improve social sustainability is still visible. By becoming more digitized, there is a strive for the human-in-the-loop process, which means that companies desire to enhance the work environment for the employees by utilizing machines to improve and ease their tasks [20]. Organizational actions toward human cyber-physical operations instead of fully automated systems have become important. This led to the development of the Operator 4.0 concept, which focuses on human-in-the-loop processes instead of fully automated [27]. Systems support humans to make faster-informed decisions. Consequently, emerging technologies and data-driven approaches can drive the redesign of traditional supply chains aiming at resource efficiency and circularity [4].

2.4 Defining the main parameters

Based on the literature review, three main parameters connected to DDDM were identified. They are (i) enablers for data-driven decisions in the manufacturing industry, (ii) the current business activities and operations towards more data-driven processes, and (iii) what companies' end goal commonly is with data-driven processes. In the first parameter, it is understood that companies must first build a digital foundation driven by new technology (such as AI, Big Data analytics, and Block chain) to utilize DDDM. A digital core is needed, i.e., by having a solid IT infrastructure, firms can utilize data at an unlimited potential. Therefore, these are the 'enablers' for DDDM. The second parameter emerges from the understanding that manufacturers are currently pressured by globalization, technology advancements, society, and competitors to enhance their current operations. Therefore, manufacturers' business activities towards more data-driven and smarter operations are apparent, leading to a paradigm shift in the industry. We refer to 'business activities' as our second parameter. In the third parameter, the end goal of companies is to achieve improved sustainable performance by optimizing the production and supply chain processes. Hence, we chose 'end goal- improved TBL performance' as our third and final parameter.

3. Methodology

Based on the aim of the study, an abductive research approach was chosen for this study. The alternation between inductive and deductive principles allowed flexibility and freedom, a critical feature in theory-building [28]. To gather a holistic understanding of the Swedish manufacturing industry regarding DDDM and TBL of sustainability, companies at different stages of their digital transformation were studied. Likewise, to generate a broad perspective on the impact of data-driven manufacturing and its effect on supply chain operations, Multi-National Enterprises (MNE) were included, and Small and Medium-scale Enterprises (SMEs) were excluded in this study. Through an internal evaluation, it was ensured that the chosen companies were at different stages in their level of digital integration. We believe academics contribute to shaping the future Swedish manufacturing industry hence, they were also included in the interviews.

The selection process of the case companies and academic institutions is presented in Figure 1. Data collection was done through literature reviews and semi-structured interviews. The reason for taking a semi-structured approach is based on Saunders et al. [29], which describes semi-structured interviews as appropriate when conducting exploratory research. It also helped in capturing new phenomena based on the respondent's answers. 14 interviews via digital meeting tools, e.g., Zoom and Microsoft Teams, were conducted with 15 respondents across industry practitioners and academics. The length of each interview lasted between 40 to 60 minutes.

The interviewees from industry practitioners were with high holding positions individuals in the respective companies such as Head of footprint design, Vice President in the supply chain, development manager, business policy expert, and sustainability manager. The type of industry they represented included hygiene and health, automotive, metallurgy, clothing, and industry experts. Concerning academics, the interviewees were Ph.D. holders within the supply chain, industrial development, and logistics in Swedish universities and two professors in their fields. The interviewed case companies are referred to as case companies A to I, experts as A1 and A2, and academics as experts B to E.

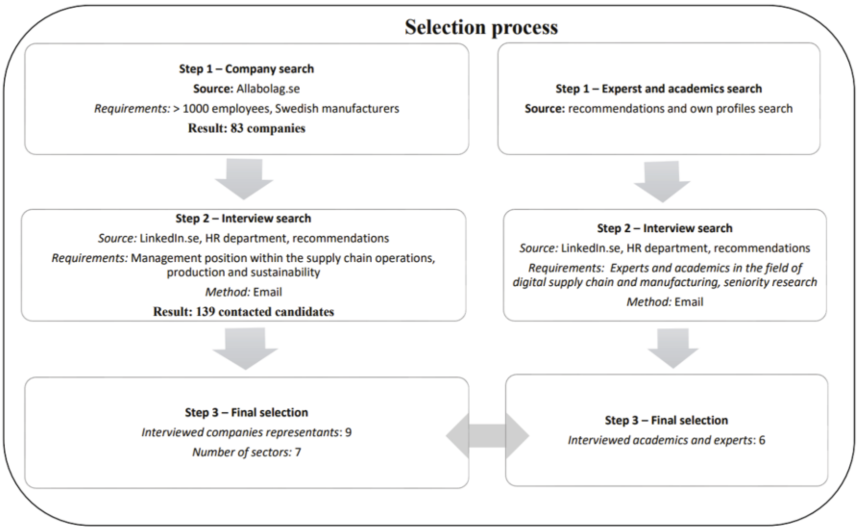

Figure 1. The selection process for the study interviewees

The interview data were manually transcribed after each interview. When the researchers were familiarized with the data, initial codes were generated. The data were color-coded to visualize the codes in the transcriptions and separate them from each other. The codes were used to search for themes. The themes could be generated more rapidly as the answers from the interviews were based on facilitating an understanding of the linkage between the parameters (see section 2.4), referred to as categories.

4. Findings

The findings in this paper come from both the two separate fields of respondents, i.e., the case companies' view and the academics' and experts' view. Table 1 summarizes the findings in terms of practitioners, academics & experts.

Table 1. Interviews findings: companies, academics, and experts

Main Findings	Practitioners	Academics & Experts
Internal & external challenges	● Standardization & Integration of IT systems ● Change management ● Excessive data ● Transparency ● Reliability ● Validity	● Data management ● Competence ● Data availability ● Regulations ● Information sharing ● Standardization of systems
Main Advantages	● Reduced bullwhip-effect ● Improved planning and troubleshooting process in the supply chain ● Improved visualization and overview over company processes	● Real-time information access ● Unlimited opportunities ● Improved competitive power ● Proactive machine-maintenance
Main Disadvantages	● Decreased understanding ● Required resources to run and update current systems	● Faulty in-data ● High costs ● Uncertain future development
Future applications & improved TBL performance	● End-to-end transparency ● Automated planning ● Optimized transportation	● Integration of intelligent technologies ● End-to-end transparency ● Real-time analysis and reactions
Data needs	● Customer data ● Uncertainty of what is needed	● Specific data for specific problems ● Clean & structured data
Value of data	● Unlimited potential ● Utilization from end-to-end in the supply chain ● Collaborating effort for TBL improvements	● Current limitations to low hanging fruits ● TBL decisions based on a complex and extensive amount of data

Subsequently, the interview data were analyzed together by coding the data. The codes were used to create themes, subsequently, categories. The categories were revised and refined to only include information on the linkage between these categories. Thus, the themes were generated and connected to the codes and the categories in the taxonomic tree in Figure 2.

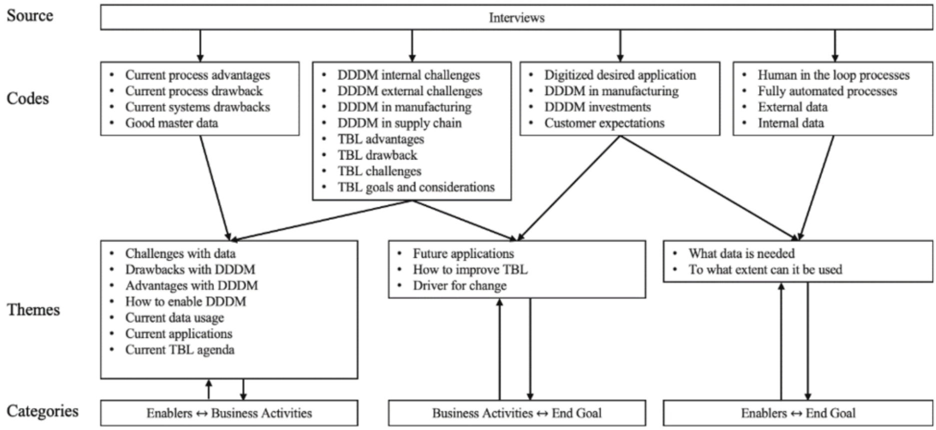

Figure 2. Taxonomic tree of the development from initial codes to final themes

The themes were further reviewed after internal and external homogeneity and heterogeneity. Themes with similarities were merged or developed into more specific themes. In this way, the themes could be linked meaningfully, and differences identified. The established themes were further used to develop the conceptual model, where the interconnectedness between the chosen parameters (section 2.4) is described.

4.1 Insights from Case companies

The case companies' three main challenges in current digital operations are standardization and integrations of IT systems, change management, and excessive data. In contrast, transparency, reliability, and validity issues can be seen as the primary external challenges. It is further essential to analyze the findings depending on the case company from the interviews. The challenges varied between the companies due to how developed they are in their digital transformation, supply chain, and size. Eight out of nine case companies found standardization and integrations of IT systems challenging; however, some companies did not have it as a top challenge. For instance, Company E did not consider standardization and integrations of IT systems the main challenge, which has come further in becoming digitized and can put more pressure on external partners to use the same type of systems. On the contrary, Company C, D, and I, who put standardization and integrations of IT systems as the main challenge, had less power to decide their suppliers' systems and had less control over the supply chain than Company, B, E, and H.

The current main advantages the case companies have experienced from data-driven processes include a reduced bullwhip-effect, improved planning, and more efficient troubleshooting processes of the supply chain. These three aspects can be seen to especially have environmental and financial impacts for companies. The most mentioned advantage is the enhanced visualization and overview of the company processes. Analyzing the improvements in the supply chain, companies have different views for the bullwhip effect, planning, and troubleshooting aspects. Decreased costs are commonly the main driver, but companies also stressed concerns about satisfying customer needs.

For Company I, reducing the bullwhip-effect and obtaining a more efficient supply chain help to achieve better customer rating.

In contrast, Company B stressed that the systems across the supply chain entities must provide a complete supply chain overview to minimize the bullwhip effect, a challenge with current systems. The cases perceive decreased understanding of specific company processes due to automation and the resources required to efficiently run and update current digital systems as the main drawbacks of data-driven systems. Companies stressed their concern over whether their data can be trusted as they lose control over the data generation. Therefore, human-in-the-loop processes were essential for the case companies to complement the data with human assessment and increase trust and understanding over data-driven systems. The companies said that their data-driven systems usually do not work as desired. Minor errors in the systems can, according to Company F, lead to extensive mistakes, which further become both an environmental and an economic drawback. In addition, according to Company E, digital systems are usually specific in what they can do, which makes it easy to overlook certain factors that the systems do not include. Consequently, human integration in the digital processes has been stressed as essential for the case companies.

4.2 Insights from academics and experts

Data management, competence, and information not always being available were found to be the main internal challenges according to the academics & experts, whereas lack of regulations, transfer competence to subcontractors, information sharing, and usage of the same system among all actors in the supply chain was seen as the primary external challenges. The academics & experts further argued that there is a need to have sufficient security and standards when investing in a digital supply chain. A challenge that often occurs among such circumstances is to find the right time to invest, as waiting too long could make the opportunity disappear, as stressed by Expert A1 and A2. The main drawbacks of data-driven systems are that people tend to enter incorrect data, the need for established regulations and standards, and high costs. The main advantages were linked with real-time information, unlimited opportunities, the enhanced life span of products, and improved competitiveness and service. The same respondents added that SMEs often do not have the same access to data as MNEs. Consequently, the smaller the customer, the lesser amount of accessible information.

Future applications are mainly driven by transparency, automated planning, and optimized transportation, which can enhance the TBL performance by primarily decreasing the need for flights and optimizing the production process. When implementing a digital supply chain, the main drivers for change were becoming more customer-centric, economic benefits, and meeting growing customer demands. Future applications are motivated by companies' interests and how governments and significant actors in the industry work towards sustainability and standardization of data systems. For instance, Expert C argued that there is often an internal initiative to become more sustainable in companies. The same respondent also explained the importance of encouragement from management to drive digitalization. Experts B and E explained that driving digitalization generally connects to improving costs, quality, delivery, and sustainability, which are the areas where data is used.

4.3 Linking the end goal with enablers for data-driven decision making

Concerning the linkage between data and TBL performance, the value capture was investigated to what data is needed and to what extent data can be used. The case interviews revealed that many different types of data can be valuable when developing sustainable strategies and that there is no limit to what data actually can do. Companies will have a better chance to apply effective data-driven systems for improved TBL performance with new intelligent technologies. Likewise, enabling real-time analysis of the supply chain and emissions can further create proactive means in the supply chain.

The data mainly needed to increase the TBL performance and capture value can be derived from customer data. Simultaneously, the case interviews revealed that most companies continuously learn what kind of data they need to become more environmentally friendly. There is no end to what data can be used for. Data integration can be utilized from end to end in a manufacturing supply chain. Hence, the primary pursuit when improving the TBL performance was found to be helping external actors with sustainability and not only improving such aspects internally. Current systems are limited to capturing value from low-hanging fruits and rely on structured data and human integration. Future data-driven systems are likely to handle complex and extensive amounts of internal and external information and thus improve TBL performance through the whole supply chain.

5. A model for sustainable data-driven decision making

Based on the interview data and literature review, in Figure 3, a conceptual model is proposed. The main parameters in DDDM identified are, 1) data and IT infrastructure, 2) current operations, and 3) an improved TBL performance. The model captures the interconnections between such parameters from the analysis of the interviews data. The model depicts the benefits and challenges of DDDM and its relation to more sustainable and resilient supply chain operations within the manufacturing industry. Literature and empirical findings agree that DDDM relies heavily on how an organization is structured, its digital solutions, and strategies. For instance, real-time data and analysis cannot be fulfilled without good communication and visibility. The same goes for improving planning, and future operations, driven by transparency. The linkages between 'Enablers' and 'Business Activities' consist of 'Challenges with data' and 'DDDM,' where the standardization and integration of IT systems, information sharing, reliability, and data validity constitute the most significant challenges. Some of the applications for DDDM have aided in reducing CO2 emission, mitigating the bullwhip effect, and improving planning, which can decrease CO2 emissions further. However, there are implications such as high cost and potential process complexity.

The link between 'Business Activities' and 'End Goal' consists of 'Future operations.' Here, the current business activities and the associated challenges work towards developing the end goal of improved TBL by further utilizing technologies to bring values for humans, society, and ecology, i.e., Industry 5.0 [13]. Lastly, the linkages between 'End Goal' and 'Enablers' consist of 'Value captured,' i.e., real-time analysis, visualization and transparency, and overall unlimited possibilities for improving sustainable performance.

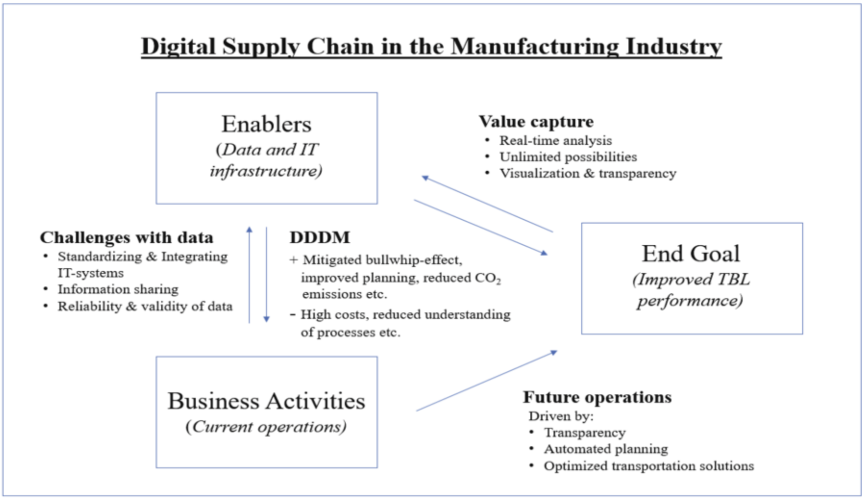

Figure 3. Conceptual Model of Data-driven decision making in the manufacturing Industry.

Furthermore, there are economic benefits in working with TBL. For instance, improved planning leads to fewer resources being exploited. End end-to-end transparency could support and ensure environmental accountability (tracking of targets, measurements, and environmental footprint) and the possibility of making sustainability a driving performance indicator in more companies. Real-time analysis is heavily linked to a mitigated bullwhip-effect, where raw materials might not be exploited to the same degree (material sustainability) and optimized transportations for reduced emissions.

Table 2 summarizes how the TBL performance can be improved, where each aspect is covered by advantages driven by future operations realized with a digital supply chain.

Table 2. Triple bottom line performance improvements.

Economic	Social	Environmental
• Reduced need for flights • Increased utilization of packaging • Avoid producing excess material • More optimized transportation • Accurate pricing • Better planning and less wasted time	• Knowledge retention • Reduced physical labor • Decreased level of rework • Enhanced trust among all actors • Improved competitiveness & service	• Lower CO2 emissions • More efficient recycling process • Re usage of energy • Enhanced life span of products

6. Conclusion and future work

To understand the standardization processes for data-driven systems, it is critical to establish unified systems and supply chain entities and consider influential industrial players, customer trends, and governmental actions. This way, companies can develop effective communication channels to transmit the necessary data to optimize transportation and generate accurate forecasts. Additionally, companies should put a significant focus on human integration in data-driven processes since this would enable companies to retain the company knowledge within its people, which is a necessary social aspect to consider. Implementation challenges must also be considered and generate structured and relevant data for current data-driven systems in use. DDDM enables sustainable supply chain operations. It increases companies' transparency, visualization, and efficient analysis system leading to improved control, flexibility, and understanding over the supply chain. The proposed model in Figure 3 illustrates the understanding of data-driven decision-making in the manufacturing industry concerning the value capture, challenges, benefits, drawbacks, and the future regarding digital supply chains and the end goal of improved TBL performance.

The limitations of this study connect to the generalization and broad approach of the study. The number of companies included was limited and comprehended diverse industries, with digital journeys driven by different goals. Likewise, this study does not include financial data and detailed metrics regarding DDDM. As a next step, we propose that the benefits, challenges, and applications described in this research could be verified in a quantified study. It is further recommended that future research explore how data-driven processes change companies' business models. This is because it has been seen that data-driven processes require improved transparency and trust between companies, which consequently could open the door for service as a business since companies would allow external companies to access their data. Lastly, as technology is continuously getting less expensive and the alternatives increase, future research should involve SMEs since this research was delimited to MNEs.

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