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The role of digital twins in shaping aviation's circular economy transformation

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Abstract

This study addresses the challenges and benefits of Digital Twin (DT) applications in the aviation industry. We conducted a systematic literature review and employed a Multi-Criteria Decision Making (MCDM) approach to identify key factors for developing a DT aligned with the circular business model, specifically for supply chain systems, production, and operations optimization. Our analysis synthesizes the major benefits and challenges, which were applied to a real-world case study involving aviation industry stakeholders. The results provide valuable insights for enhancing aviation processes through DT technology.

Keywords: Digital Twin, Circular Economy, Aircraft Industry, Sustainability

1. Introduction

The aircraft manufacturing industry occupies a significant position within the global economy, holding the largest share of the manufacturing sector (Scheelhaase et al., 2022). This sector faces complex challenges throughout its operations, and the establishment of a resilient supply chain is crucial for mitigating disruptions and ensuring continuous production. Achieving a balance between production and operational capabilities to meet market demands while adhering to strict safety and quality standards is an ongoing challenge (Zutin et al., 2022). It is also important to align production processes with environmental sustainability goals to reduce emissions and improve efficiency, investing in sustainable technologies (Jensen et al., 2023). The industry's ability in addressing these challenges is not only crucial for promoting innovation, but also for assuming responsibility for environmental conservation (Zutin et al., 2022; Jensen et al., 2023).

With the rise of such concepts as "Industry 4.0", the desire for transformation has become a focus in the aviation industry. With advancements in technologies like the Internet of Things (IoT), Artificial Intelligence (AI), cloud computing, edge computing, Big Data, and 5G, it is now possible to manage products and business processes as well as maintenance operations more effectively throughout the entire life cycle of an airplane (Xiong and Wang, 2022). In this context, Digital Twins (DTs) play an important part in manufacturing, as they allow real-time monitoring, optimization, and simulation of production processes towards enhanced equipment performance (Gao et al., 2022; Soori et al., 2023; Pietrangeli et al., 2023). A DT serves as a representation of a physical system, something that is achieved by combining data analytics, machine learning, and multi-physics simulation. DTs have proven to be valuable in predicting issues, improving operations, and increasing efficiency across industries operating in fields crucial for green energy (Rivas Pellicer et al., 2023). Related opportunities refer to cost reduction and more informed management (Lanzini et al., 2023). In the aviation industry, a resilient supply chain supported by DTs can mitigate disruptions. For instance, DTs enable predictive maintenance by continuously monitoring aircraft components, predicting failures before they occur, and scheduling maintenance proactively to minimize downtime. This approach ensures that the supply chain remains robust, reducing the impact of unexpected events on production schedules. Furthermore, integrating real-time sensor data with Computer-Aided Design (CAD) models and simulations allows manufacturers to optimize core production processes with precise data-driven decisions (Hunde and Woldeyohannes, 2022; Soori et al., 2023). This integration enhances operational efficiency and cost-effectiveness, further strengthening the aviation industry's capability to meet evolving market demands while maintaining high standards of safety and sustainability.

In this research, we conduct a comprehensive analysis of literature on DT applications to formally identify the key factors and indicators required for developing a DT that optimizes supply chain systems, production, and operations in the aviation industry, with a special focus on those aligned with the circular business model. We will initialize the study by analyzing the literature to identify the major benefits and challenges associated with building a DT of the aviation manufacturing process. After formalizing these factors, we aim to discern the sub-set of critical benefits and challenges that are essential to such an aim. This result will be achieved by means of the use of a Multi-Criteria Decision Making (MCDM) approach. In a subsequent section of our study, we are going to identify the most important indicators required to build a DT of the Aviation Manufacturing process,including all the relevant stakeholders, ranging from the original equipment manufacturer to Tier-1 and Tier-2 suppliers.

The structure of this paper is outlined as follows. In Section 2, we conduct a comprehensive literature review. Section 3 provides a detailed account of our methodological approach. In Section 4, we present the case study, accompanied by a discussion of the results and the key managerial insights derived from it. Section 5 is dedicated to discussing the conclusions, with an emphasis on potential avenues for future research development.

2. Literature review

DTs made their initial debut in the 1970s during the Apollo Program by the National Aeronautics and Space Administration (NASA). Dr. Michael Grieves is credited with the inaugural application of the DT concept in 2002. In 2010, NASA described the essential components of DT. In 2012, the Air Force Research Laboratory (AFRL) introduced the concept of Airframe Digital Twin (ADT) for the design and maintenance of airframes through an integrated system (Xiong and Wang, 2022).

The following approach has been developed to carry out the literature review:

- reviewing existing works on DT implementation in the context of circular economy;
- understanding assembly for DT in the aircraft/aviation industry, so as to gain insights from related works focused on particular systems;
- reviewing existing works on circular economy models implementation in the aircraft/aviation industry.

Various studies have been focused on DT implementation in the context of circular economy. Preut et al. (2021) presented the potential contributions of digital twins to the circularity of products and the management of circular supply chains. The authors concluded that circular supply chains can benefit from digital twins but there is still a need for research and development, particularly regarding product and use case-specific implementations of the concept. A Life Cycle Assessment (LCA)-based industrial optimization framework was proposed by Barni et al. (2018). In this framework, the developed DTs collected data from the field and evaluated the sustainability performance of both existing and planned production mixes.

The concept of DTs in the context of manufacturing processes and their potential utility in enhancing operational efficiency and cost reduction was elucidated by Soori et al. (2023), as it pertains to the innovative integration of digital replicas within manufacturing processes to optimize efficiency and curtail operational costs. Xiong and Wang (2022) provided an in-depth examination of DTs within the aviation industry. Their work developed a thorough historical overview of DTs, insights on the intersection of DTs and the aviation sector, and a forward-looking exploration of potential future applications. Meyer et al. (2022) systematically outlines the diverse prerequisites necessary for the successful implementation of DTs in the aircraft industry. Li et al. (2021) analyzed the complexities of digital twin technology within the aerospace community. By doing so, the paper aims to assist in rectifying the errors that can impede the effective implementation of safety-critical systems, thus contributing to enhanced safety and reliability in this domain. The application of DT in aerospace was discussed by Wang et al. (2020). The authors first introduced fundamental concepts pertaining to DTs, discussed the significance of DT in aerospace applications, and subsequently provided an overview of the ongoing research landscape concerning DT technology within China's aerospace sector. In (Meyer et al., 2020) It was documented that the German Aerospace Center (DLR) initiated a project aimed at investigating methods, technologies, and processes for DTs. Within this project, three specific use cases were described: a) the virtual product house, b) the virtual engine, and c) the research aircraft. The researchers directed their focus towards a range of information technology-related concerns, including the key project components, such as a) DT, b) digital threads, c) application layer, and d) the common DT vision. Moenck et al. (2023) analyzed the diverse domains where the digital twin concept finds application. Additionally, they shed light on the integrational, organizational, and compliance-related challenges and opportunities that pertain to aircraft production within this context.

Shi et al. (2021) introduced the technical approach while elaborating on the system architecture of an intelligent assembly integration platform that relies on the digital twin concept. This work focuses on the innovative techniques and infrastructure designed to facilitate intelligent assembly processes, utilizing the DT as a central framework. Zhuang et al. (2021) stated the requirements for dynamic data management and process traceability in complex products such as satellites, missiles, and aircraft. The authors introduced a comprehensive framework for managing assembly data through DT and concurrently devised the DT-based Assembly Process Management and Control System (DT-APMCS) to empirically validate the efficacy of this proposed framework. Ibrion et al. (2019) called the attention to the inherent risks associated with the implementation of DTs within the Marine Industry, drawing valuable insights from the experiences of the Aviation Industry. In their research, the authors conducted an in-depth analysis of a case study involving the Boeing 737 MAX crashes in Indonesia and Ethiopia. They arrived at the conclusion that while Digital Twins offer numerous advantages, their implementation is not without a significant degree of uncertainty and associated risk.

With a specific emphasis on targeted systems, Singh et al. (2021) developed an Information Management (IM) framework tailored for DTs. This framework comprises four key IM phases: information identification, information processing and storage, information aggregation, and information retrieval and retention. Furthermore, the information flow across the physical, data, and model layers was studied. The resultant framework holds the potential to find practical applications across various stages of the aircraft life cycle. Wu and Li (2021) introduced a dynamic data-driven framework tailored for DTs in the context of complex engineering products. To illustrate the practicality of this framework, a case study was conducted, focusing on health management of an aircraft engine. The proposed framework modeled the DT by extracting data from an array of sensors and Industry Internet of Things (IIoT) sources. It further facilitated the real-time monitoring of the Remaining Useful Life (RUL) of the engine. Additionally, the study proposed the application of a Long Short-Term Memory (LSTM) neural network to dynamically update the DT, enabling continuous evaluation of the current RUL of the physical aircraft engine. Mandolla et al. (2019) introduced the concept of DTs within the realm of Additive Manufacturing (AM) Supply Chains. Their focus was on the management and security of data generated throughout the entire process of fabricating metal aircraft components using AM technology. Also, the authors highlighted the potential of integrating blockchain technology with robust system infrastructure to drive substantial and transformative changes across various sectors, with particular relevance to the aviation industry. In order to improve the efficiency of the aircraft assembly process, citezhang2022digital introduced a Digital Thread-based modeling Digital Twin (DTDT) framework, comprising five distinct modules. The practical application of this framework is exemplified through a case study focused on the drilling and riveting processes within aircraft assembly. Ren et al. (2023) introduced a Digital Twin (DT)-enabled approach for Aircraft Final Assembly (AFAL). They also proposed a DT-assisted framework, known as DT-assisted Heterogeneous Processes Coordination (DT-HPC), designed to effectively manage diverse devices and resources. Considering that the Aircraft Final Assembly Line (AFAL) constitutes a complex manufacturing system where multiple installation and testing processes occur concurrently at individual workstations, the proposed algorithms have the capability to conserve energy while ensuring the fulfillment of distinct Quality-of-Service (QoS) requirements. A DT system, designed for the purpose of monitoring and assessing the operational condition of reconfigurable tooling in aircraft production, was developed by Jin et al. (2023), and subsequently validated through assembly experiments. Kosova and Unver (2023) introduced a DT-based health monitoring system, which employs machine learning techniques to facilitate the early detection of system failures during the design phase. This research specifically focused on hydraulic systems at the aircraft level, covering a range of twenty failure scenarios.

The exploration of Circular Economy within the aircraft/aviation Industry has been a relatively underexplored area in research. However, a few selected researchers have made significant contributions in this domain. Dias et al. (2022) led a comprehensive investigation to identify and analyze circular economy-related practices relevant to the aerospace industry. The study proposed an assessment of these practices within three global companies engaged in the development and manufacturing of aerospace products. The outcome of this research effort is a valuable guidance framework for the adoption of circular economy practices tailored to the unique industrial requirements. Markatos et al. (2023) performed a sensitivity analysis on an integrated MCDM Model for sustainability assessment. Their work involved the implementation of a hybrid MCDM tool aimed at aiding the selection of sustainable materials in aviation. The robustness of this tool was tested and validated through an extensive sensitivity analysis, formalizing considerations on its practical applicability.

We herein conducted a thorough analysis of recent research papers to examine the challenges and benefits of DT-based applications in the aviation industry. We have summarized the key findings in Tables 1 and 2, providing a clear and concise overview of the main insights from the existing literature. The application of a MCDM approach to analyze the interdependencies between challenges and benefits holds the potential for several positive outcomes, representing a novel perspective in literature.

Table 1. Challenges in DT implementation

ID	Description	References
C_1	**Uncertainty in creating an actual environment or scenario:** uncertainty may arise from incomplete or inaccurate data, unexpected variables, or complex interactions. Capabilities of DT may be limited given difficulties to replicate the actual environment.	Jyeniskhan et al. (2023)
C_2	**Difficulty in predicting safety levels for performance optimization:** accurate prediction of safety thresholds becomes challenging while deploying DTs in safety-critical fields like aerospace.	Perno et al. (2022)
C_3	**Unreliability of real-time input data:** accurate real-time input data is essential for DT implementation, and failing to collect reliable data can harm decision-making and the analysis process of DT.	Jyeniskhan et al. (2023)
C_4	**Challenges in implementing complex supply chain processes:** manufacturing industries operate in an uncertain and constantly changing environment as per product design and processing technologies.	Singh et al. (2018)
C_5	**Complexity of risk assessment requirements for DT implementation:** risks identification, analysis and prioritization are important for management, something that can be a complex and uncertain process.	Millwater et al. (2019)
C_6	**Cyber security issues:** physical assets for which one can envision digital twins will require a high level of safety and security.	Rasheed et al. (2020)
C_7	**Complexity of compatible structure:** DT involves handling the complexity of data integration, ensuring seamless interoperability and addressing data accuracy challenges.	Jyeniskhan et al. (2023)
C_8	**Precision and accuracy related challenges:** challenges associated with the resolution of sensor data and latency in communication between a physical device and its DT.	Rasheed et al. (2020)
C_9	**Data management and processing related challenges:** they refer to such issues as data transfer, data storing, and data quality.	Jyeniskhan et al. (2023)
C_{10}	**Data security related challenges:** they involve data protection and data privacy.	Jyeniskhan et al. (2023)
C_{11}	**Model related issues:** issues such as communication and combination between models, as well as interoperability may arise while working with different models.	Jyeniskhan et al. (2023) and Sharma et al. (2022)
C_{12}	**Complications in integrating system and IT infrastructure:** big data and complex infrastructure require high computational power, time, and speed for the DT model to operate in optimal conditions.	Jyeniskhan et al. (2023) and Attaran and Celik (2023)
C_{13}	**Large-scale computation:** handling massive volumes of data, complex algorithms, and real-time processing requirements, as well as integrating diverse systems while ensuring robust data security increase computational complexity.	Rasheed et al. (2020) and VanDer-Horn and Mahadevan (2021)
C_{14}	**Lack of standards, frameworks, and regulations:** DTs are limited due to a lack of standards and recognized interoperability, especially in the manufacturing domain.	Botín-Sanabria et al. (2022)

Table 2. Benefits of DT implementation

ID	Description	References
B_1	**Enhanced Predictive Maintenance:** by creating a replica of machinery and simulating different failure scenarios, DT aids to predict when maintenance is required, minimizing downtime and related costs.	Mohsen and Gokhan (2023)
B_2	**Safety enhancement:** risks can be identified and reduced in various areas, including product availability and reputation.	Rasheed et al. (2020)
B_3	**Improved productivity and efficiency:** operations can be optimized in terms of productivity and waste reduction by simulating processes for identifying bottlenecks and inefficiencies of manufacturing systems.	Soori et al. (2023)
B_4	**Enhanced quality control:** DT can detect abnormalities via real-time tracking, lowering risks of defects in finished products.	Soori et al. (2023)
B_5	**Reduced production cost:** DT can reduce cost by identifying opportunities for optimization, as it helps to save money on materials, energy, and labor costs.	Soori et al. (2023)
B_6	**Efficient supply chain:** real-time analytic and predictive alerts are addressed in supply chains, leading to informed decision-making and containing heavy losses.	Sharma et al. (2022)
B_7	**Increased Cross-functional collaboration:** DT can collect data over time by providing insights into product/machine performance and end-user experience.	Mohsen and Gokhan (2023)
B_8	**Increased operational efficiency:** DT can simulate different scenarios of a manufacturing process and enhance Operational Equipment Efficiency (OEE) by optimizing downtime and performance.	Mohsen and Gokhan (2023)
B_9	**Improved product development:** DT supports product development while also helping in reducing the cost related to this stage.	Botín-Sanabria et al. (2022)
B_{10}	**Optimized product life cycle:** DT is effective in improving product life cycles by real-time monitoring of all sub-components and joints throughout the whole useful life.	Sharma et al. (2022)
B_{11}	**Improved decision support system:** availability of quantitative data and advanced real-time analytics assist in making more informed and faster decisions.	Rasheed et al. (2020)
B_{12}	**Enchanced personalization of products and services:** with detailed historical requirements, preferences of various stakeholders, and evolving market trends and competitions.	Rasheed et al. (2020)
B_{13}	**Smart production network:** connected cyber-physical production systems will form a global production network that can respond real-time to dynamic changes in local production systems and external interactions with supply chains.	Lu et al. (2020)
B_{14}	**Improved customer satisfaction:** DT can assist in improving customer satisfaction by better understanding customer needs, developing existing products, operations, services, and helping drive new avenues for business innovation.	Mohsen and Gokhan (2023)

By utilizing MCDM techniques, it becomes possible to systematically weigh and prioritize various factors that influence both challenges and benefits within a given context, such as the aviation industry (Dožić, 2019). This structured approach enables decision-makers to make informed and data-driven choices, thereby enhancing the efficacy of strategies and solutions. Additionally, the use of MCDM can lead to a more comprehensive understanding of the trade-offs involved in addressing these challenges and realizing the associated benefits. It allows for a holistic assessment that takes into account a multitude of factors, ultimately aiding in the formulation of more robust and balanced strategies that align with the broader objectives of the aviation sector (Chai and Zhou, 2022).

Our aim is to fill in a gap in literature by proposing the use of a suitable MCDM approach to evaluate the most significant challenges and benefits related to DT implementation in the aviation sector within the circular economy framework.

3. Methodological approach

We suggest the use of the Decision-Making Trial and Evaluation Laboratory (DEMATEL) for analyzing the interdependencies within the sets of challenges and benefits in the context of aviation formalized in Tables 1 and 2. Primarily due to its unique capacity to uncover causal relationships and provide a structured understanding of complex issues, DEMATEL goes beyond traditional MCDM methods. It allows us to identify the cause-and-effect relationships between variables, offering insights into the root causes of challenges and their impact on the overall system. This attribute is particularly valuable in aviation, where several interactions among factors can have far-reaching consequences. DEMATEL's ability to visualize and quantify these relationships can lead to more informed and effective decision-making compared to other techniques. DEMATEL's distinctive advantage lies in its ability to analyze hidden connections within the system, providing a deeper comprehension of the challenges and benefits, which can be instrumental in crafting well-informed and targeted strategies for improvement. A comprehensive description of the main methodological steps is recalled in the following (Aiello et al., 2021).

- **Data collection and transformation**. Collect input data from experts regarding the causal relationships among n factors, compared in pairs. These relationships are often expressed in linguistic terms. Translate the linguistic variables of influence into numerical values according to the following scale: 0 (No Influence), 1 (Very Low Influence), 2 (Low Influence), 3 (Medium Influence), 4 (High Influence), 5 (Very High Influence). If more than one expert is involved in the process of data collection, a squared $n \times n$ matrix for each expert has to be produced, all of them to be integrated into a single squared input matrix (also called, direct-relation matrix A) before proceeding to the next step.
- **Normalized matrix calculation**. Calculate the normalized matrix $D = s * A$, by using the value s, calculated as follows:

$$s = min\left[\frac{1}{max_{1\leq i\leq n}\sum_{j=1}^{n} a_{ij}}, \frac{1}{max_{1\leq j\leq n}\sum_{i=1}^{n} a_{ij}}\right] \quad (1)$$

- **Total relation matrix calculation**. Calculate the total relation matrix T by considering the identity matrix I and performing the multiplication between the normalized matrix D and the inverse of the difference between matrices I and D, as follows:

$$T = D \times (I - D)^{-1}. \quad (2)$$

  By means of this iteration process, matrix T will incorporate direct and indirect effects charactering the dataset of interest.
- **Causal relation map**. Produce the causal relation map based on the values in the total relation matrix to identify the most influential elements and discriminate them based on their prominence and relation values. Prominence and relation values are respectively calculated as $r_i + c_i$ and $r_i - c_i$, where r_i and c_i are defined as $n \times 1$ and $1 \times n$ vectors, representing the sum of rows and sum of columns of matrix T. In the causal relation map, factors with higher values of prominence are those factors that most significantly impact the problem under study. Additionally, factors with positive relation values can be considered as net causers, while factors with negative relations are considered as net receivers (Du and Shen, 2023). The causal relation map serves as a visual tool to analyze and illustrate the causal relationships among the factors, providing a clear distinction between the most influential and prominent elements.

4. Case Study

The present case study iterates the DEMATEL application aiming at identifying the most prominent challenges and benefits of DT implementation in the sector of reference, among those presented in Tables 1 and 2. Specifically, we led several brainstorming sessions to generate two linguistic input matrices, reported in Tables 3 and 4. We double-checked the attributed linguistic evaluations with the support of aviation industry stakeholders, external to the analysis and with varied professional backgrounds (Yontar, 2023). In detail, Table 3 reports the linguistic input matrix for the challenges described in Table 1, and Table 4 reports the linguistic input matrix for the benefits described in Table 2. The diagonal elements are invariably set to NI, denoting self-comparisons. These linguistic input matrices serve as the foundation for the DEMATEL implementation, enabling a comprehensive understanding of the interplay among the elements of the framework.

Table 3. Linguistic input matrix for challenges

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}
C_1	NI	H	L	VH	L	H	M	H	L	M	M	M	VL	VL
C_2	M	NI	VL	M	H	VH	L	VL	L	H	M	M	L	M
C_3	H	VH	NI	M	M	M	NI	L	VL	NI	M	VL	H	L
C_4	L	M	L	NI	L	VL	M	L	VL	NI	VL	NI	NI	L
C_5	H	M	L	H	NI	H	M	L	M	VL	M	H	M	M
C_6	L	M	VL	H	NI	NI	L	VL	H	VH	L	VL	NI	VL
C_7	M	H	L	M	L	VL	NI	M	VH	L	VL	H	M	L
C_8	H	VH	VH	L	M	M	H	VL	M	L	H	M	H	VL
C_9	H	VL	L	M	NI	VH	H	H	NI	H	H	M	VH	VL
C_{10}	L	VL	L	M	H	VH	L	VL	VL	NI	NI	H	H	M
C_{11}	L	L	VL	H	VL	VL	M	VH	H	H	NI	H	M	NI
C_{12}	NI	NI	NI	M	H	M	M	H	M	H	L	NI	H	M
C_{13}	NI	NI	NI	M	M	H	H	L	M	M	M	M	NI	L
C_{14}	M	M	M	M	H	VH	H	M	H	VH	H	H	H	NI

Table 4. Linguistic input matrix for benefits

	B_1	B_2	B_3	B_4	B_5	B_6	B_7	B_8	B_9	B_{10}	B_{11}	B_{12}	B_{13}	B_{14}
B_1	NI	VH	H	H	VL	H	NI	H	VL	VL	VH	NI	M	NI
B_2	VH	NI	H	L	M	H	NI	VH	M	H	M	VL	H	NI
B_3	M	M	NI	H	VH	VH	H	VH	NI	H	M	NI	H	M
B_4	H	M	H	NI	H	M	H	H	M	M	H	H	H	VH
B_5	H	H	VH	H	NI	H	M	VH	L	M	M	H	VH	M
B_6	VH	M	VH	L	H	NI	H	VH	H	H	H	H	M	VH
B_7	H	VH	H	H	L	H	NI	M	L	VL	H	M	H	H
B_8	M	M	VH	H	M	M	NI	NI	M	L	VL	L	H	L
B_9	NI	H	M	M	VH	L	VL	VL	NI	M	M	H	L	H
B_{10}	NI	M	L	M	H	L	NI	L	VL	NI	NI	L	M	H
B_{11}	H	VH	H	H	H	M	L	H	M	L	NI	VL	M	H
B_{12}	NI	M	H	M	VH	H	L	VL	H	M	NI	NI	L	VH
B_{13}	H	H	H	M	H	VH	H	M	M	L	H	VL	NI	H
B_{14}	NI	NI	NI	H	M	L	VL	NI	M	L	VL	H	M	NI

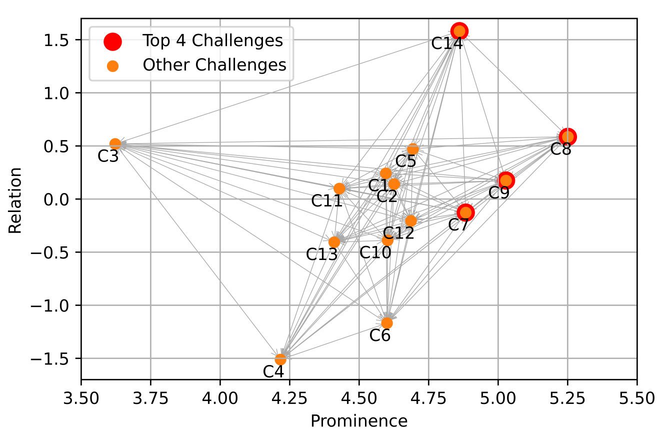

Figure 1. Causal relation map for challenges

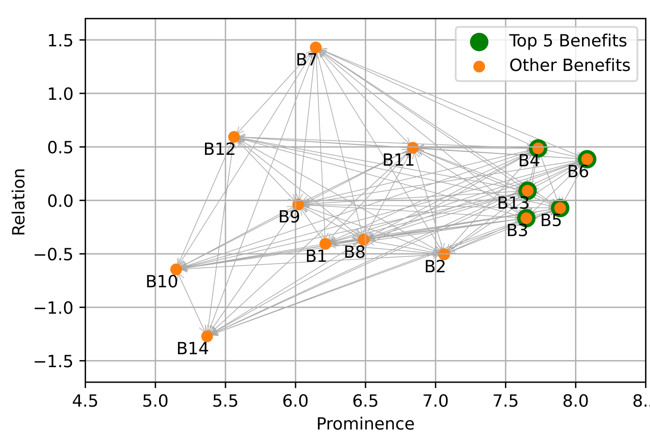

Figure 2. Causal relation map for benefits

Following the methodological implementation, the resulting total relation matrices for challenges and benefits are respectively reported in Table 5 and 6, along with related values of prominence and relation for each of the analyzed elements. Visualization of results has been carried out by producing various graphs for accurate analysis of challenges and benefits. We report a description of the produced graphs in the following.

- **Causal relation map for challenges**. The causal relation map for challenges reported in Figure 1, has been obtained by mapping the prominence and relation values for challenges and by graphically displaying their interconnections through directed arrows. Challenges associated with a positive value of relation can be characterised as net causers, while challenges associated with a negative value of relation can be characterized

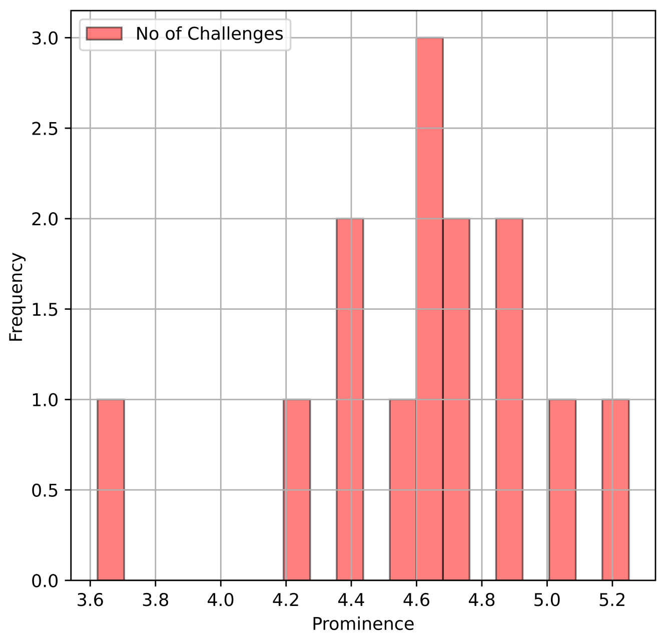

Figure 3. Prominence histogram for challenges

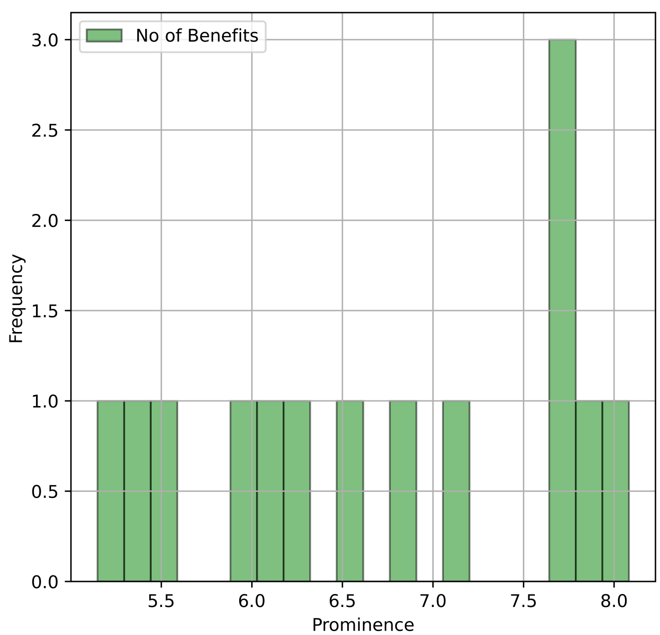

Figure 4. Prominence histogram for benefits

as net receivers. By observing this graph, it is clear that there are some highly prominent challenges, that are C_7 (complexity of compatible structure), C_9 (data management and processing-related challenges), C_8 (precision and accuracy-related challenges), and C_{14} (lack of standards, framework, and regulations). These challenges are then recognized to be the ones with the highest importance, being strongly interrelated with all the other challenges belonging to the input dataset.

- **Causal relation map for benefits**. The causal relation map for benefits reported in Figure 2, has been obtained by mapping the prominence and relation values for benefits and by graphically displaying their interconnections through directed arrows. Benefits associated with a positive value of relation can be characterised as net causers, while benefits associated with a negative value of relation can be characterized as net receivers. We can observe as there are some highly prominent benefits, that are B_6 (efficient Supply chain), B_5 (reduced production cost), B_3 (improved productivity and efficiency), B_{13} (smart production network), and B_4 (enhanced quality control). These benefits are then recognized to be the ones with the highest importance.
- **Prominence histogram for challenges**. The prominence histogram for challenges, reported in Figure 3, depicts the frequency of the prominence level for the analyzed challenges. It is clear from the graph that the maximum number of challenges lies between the prominence intervals ranged from 4.50 to 4.75. Challenges in this range are: C_6 (cyber security issues), C_{10} (data security related challenges), C_{12} (complications in integrating system and IT infrastructure), C_1 (uncertainty in creating an actual environment or scenario), C_2 (difficulty in predicting safety levels for performance optimization), and C_5 (complexity of risk assessment requirements for DT implementation). All these challenges should also be considered for a smooth DT implementation.
- **Prominence histogram for benefits**. The prominence histogram for benefits, reported in Figure 4, depicts the frequency of the prominence level for the analyzed benefits. It is clear from the graph that the maximum number of benefits lies between the prominence intervals ranged from 7.125 to 7.50. Benefits in this range are the previously mentioned B_3 (improved productivity and efficiency), B_{13} (smart production network), and B_4 (enhanced quality control). All these benefits had already been highlighted as strongly prominent in Figure 2. In the comparison between the prominence levels of benefits and challenges, it becomes evident that benefits hold a higher degree of significance. This observation suggests that the implementation of the DT places greater emphasis on its advantages rather than its challenges.

5. Conclusions and future lines

The emergence of Industry 4.0 is facilitating a profound transformation characterized by significant technological advancements across diverse sectors of activity. Within the aviation industry, where paramount importance is placed on safety and quality, the adoption of DTs poses a complex challenge. Furthermore, integrating production processes with sustainability objectives and embracing a circular business model to improve efficiency further complicates this transformative journey.

Table 5. Total relation matrix for challenges along with related values of Prominence ($r_i + c_i$) and Relation ($r_i - c_i$)

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	$r_i + c_i$	$r_i - c_i$
C_1	0.117	0.199	0.123	0.247	0.151	0.227	0.190	0.199	0.167	0.189	0.171	0.185	0.145	0.108	4.596	0.242
C_2	0.170	0.115	0.100	0.211	0.186	0.247	0.171	0.141	0.168	0.211	0.169	0.187	0.162	0.145	4.626	0.140
C_3	0.175	0.199	0.069	0.191	0.154	0.191	0.117	0.144	0.130	0.117	0.160	0.130	0.180	0.113	3.622	0.519
C_4	0.109	0.131	0.088	0.086	0.102	0.106	0.132	0.109	0.094	0.074	0.087	0.075	0.072	0.088	4.217	-1.512
C_5	0.198	0.185	0.126	0.241	0.118	0.239	0.202	0.174	0.198	0.165	0.181	0.214	0.191	0.151	4.693	0.471
C_6	0.122	0.141	0.080	0.184	0.080	0.110	0.133	0.107	0.164	0.190	0.117	0.112	0.092	0.083	4.600	-1.169
C_7	0.172	0.191	0.120	0.207	0.151	0.175	0.134	0.182	0.221	0.171	0.136	0.205	0.186	0.126	4.883	-0.128
C_8	0.217	0.241	0.194	0.224	0.193	0.242	0.235	0.169	0.214	0.199	0.217	0.215	0.231	0.126	5.251	0.586
C_9	0.197	0.148	0.127	0.222	0.120	0.256	0.221	0.211	0.141	0.221	0.197	0.197	0.230	0.112	5.028	0.174
C_{10}	0.137	0.122	0.108	0.192	0.175	0.230	0.156	0.125	0.135	0.117	0.101	0.188	0.185	0.137	4.603	-0.389
C_{11}	0.146	0.148	0.100	0.217	0.127	0.163	0.186	0.214	0.196	0.199	0.106	0.198	0.181	0.084	4.429	0.098
C_{12}	0.109	0.109	0.080	0.198	0.180	0.200	0.186	0.191	0.181	0.200	0.145	0.123	0.198	0.140	4.687	-0.206
C_{13}	0.096	0.097	0.070	0.184	0.148	0.200	0.190	0.143	0.169	0.170	0.150	0.167	0.107	0.111	4.410	-0.407
C_{14}	0.211	0.214	0.166	0.262	0.225	0.299	0.254	0.223	0.250	0.274	0.228	0.251	0.248	0.117	4.861	1.580

Table 6. Total relation matrix for benefits along with related values of Prominence ($r_i + c_i$) and Relation ($r_i - c_i$)

	B_1	B_2	B_3	B_4	B_5	B_6	B_7	B_8	B_9	B_{10}	B_{11}	B_{12}	B_{13}	B_{14}	$r_i + c_i$	$r_i - c_i$
B_1	0.155	0.260	0.260	0.238	0.199	0.246	0.105	0.248	0.143	0.156	0.231	0.111	0.227	0.160	5.769	-0.293
B_2	0.256	0.194	0.283	0.226	0.257	0.269	0.116	0.283	0.192	0.225	0.212	0.145	0.265	0.181	6.649	-0.445
B_3	0.249	0.273	0.240	0.289	0.317	0.313	0.206	0.310	0.161	0.245	0.235	0.152	0.296	0.262	7.404	-0.311
B_4	0.275	0.293	0.330	0.238	0.325	0.300	0.216	0.306	0.230	0.244	0.265	0.236	0.313	0.318	7.410	0.368
B_5	0.282	0.314	0.355	0.312	0.258	0.323	0.203	0.331	0.215	0.249	0.253	0.236	0.335	0.286	7.720	0.183
B_6	0.299	0.303	0.359	0.287	0.336	0.256	0.220	0.333	0.253	0.270	0.273	0.242	0.307	0.326	7.704	0.423
B_7	0.265	0.308	0.311	0.289	0.270	0.299	0.134	0.274	0.200	0.195	0.254	0.203	0.294	0.280	5.718	1.434
B_8	0.208	0.231	0.283	0.248	0.245	0.239	0.113	0.179	0.184	0.182	0.167	0.158	0.252	0.207	6.389	-0.599
B_9	0.149	0.243	0.242	0.227	0.278	0.216	0.126	0.190	0.129	0.197	0.192	0.196	0.214	0.242	5.443	0.238
B_{10}	0.113	0.181	0.178	0.184	0.213	0.172	0.083	0.166	0.117	0.107	0.106	0.131	0.189	0.199	4.968	-0.689
B_{11}	0.258	0.301	0.304	0.283	0.296	0.274	0.165	0.286	0.210	0.208	0.176	0.165	0.272	0.271	6.353	0.586
B_{12}	0.152	0.229	0.264	0.232	0.283	0.255	0.149	0.194	0.204	0.202	0.146	0.131	0.219	0.265	5.363	0.485
B_{13}	0.270	0.298	0.318	0.278	0.309	0.321	0.209	0.281	0.219	0.217	0.260	0.174	0.229	0.285	7.255	0.080
B_{14}	0.099	0.120	0.131	0.189	0.185	0.158	0.096	0.115	0.146	0.133	0.114	0.161	0.174	0.123	5.349	-1.461

Our research aims to explore both the benefits and challenges associated with the integration of DTs in the aviation domain by first leading a comprehensive literature review in this field. Furthermore, a MCDM approach based on DEMATEL methodology is proposed, yielding comprehensive insights that culminate in practical conclusions.

As emerged in our study, the implementation of DTs in the aviation industry brings forth significant advantages, including an efficient supply chain, reduced production costs, enhanced quality control, a smart production network, and improved overall productivity and efficiency. However, this process presents notable challenges related to such aspects as precision and accuracy, data management and processing, lack of standards, frameworks and regulations, and complexity of compatible structure.

Looking ahead, we aim to explore the key benefits and challenges uncovered in this study by converting these insights into practical guidelines for the effective implementation of DTs in aviation manufacturing and introducing a multi-expert decision-making model. This model will be designed to gather diverse viewpoints, providing a clear framework that can be applied in real-world scenarios. Future research directions may focus on further validating the MCDM approach based on DEMATEL methodology across different segments of the aviation industry, such as Maintenance, Repair, and Overhaul (MRO), and air traffic management systems. Additionally, expanding the scope to include the integration of emerging technologies like artificial intelligence and blockchain in conjunction with DTs may be interesting for understanding how to further enhance operational efficiency and safety.

Furthermore, the proposed approach could be extended to other sectors beyond aviation, such as automotive manufacturing, healthcare, and energy production. Adaptations would address sector-specific challenges and opportunities, promoting sustainability and innovation. Exploring these applications would enable us to contribute to broader discussions on digital transformation and circular economy principles in different industrial contexts. In this way, comprehensive guidance and tools could be elaborated so as to empower decision-makers when navigating DT integration across global industries.

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