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Decision-making modeling for Digital Twin implementation in the circular economy within the aviation sector

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Corresponding Author:	Silvia Carpitella California State University Northridge UNITED STATES
First Author:	Akram Pattan
Order of Authors:	Akram Pattan
	Madhura Bhandigani
	Salvatore Quaranta
	Silvia Carpitella
	Giuseppe Aiello
	Antonella Certa
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Suggested Reviewers:	Bruno Brentan brentan@ehr.ufmg.br
	Simon Nadeem s.nadeem@derby.ac.uk

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Akram Pattan[1], Madhura Bhandigani[1], Salvatore Quaranta[2], Silvia Carpitella[1], GiuseppeAiello[2], and Antonella Certa[2]

[1]Department of Manufacturing Systems Engineering and Management, California State University, Northridge
[2]Department of Engineering, University of Palermo

Dear Editor,

It is our pleasure to submit an original manuscript for considering publication in Engineering Applications of Artificial Intelligence.

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Given that Artificial Intelligence (AI) is playing a major role in the fourth industrial revolution and we are seeing a lot of evolution in various machine learning methodologies, this paper aligns well with the journal's scope. It demonstrates a novel application of AI methods in engineering by employing Digital Twins for real-world applications in aviation, and the findings are validated through rigorous analyses, ensuring replicability of the research results, thereby contributing valuable insights to the field of AI-driven engineering solutions.

We hope our work will be positively considered for publication in Engineering Applications of Artificial Intelligence.

Sincerely,
The Authors

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Akram Pattan[1], Madhura Bhandigani[1], Salvatore Quaranta[2], Silvia Carpitella[1], Giuseppe Aiello[2], and Antonella Certa[2]

[1]Department of Manufacturing Systems Engineering and Management, California State University, Northridge; 18111 Nordhoff St, Northridge, CA 91330, United States

[2]Department of Engineering, University of Palermo; Viale delle Scienze, 90128 Palermo, Italy

Abstract

This paper offers a comprehensive examination of the potential benefits and challenges associated with the adoption of Digital Twins in the aviation industry, with a particular emphasis on advancing sustainability objectives. We propose an adaptable methodological framework designed to support aviation's transition towards circular business models, specifically in the realm of commercial aircraft fleet management. Through a thorough analysis of expert insights and literature, we identify key factors influencing the successful implementation of Digital Twins. Furthermore, we explore the prioritization of sensor deployment based on principles of the circular economy, aimed at maximizing benefits while minimizing barriers. Our findings highlight the critical role of motion sensors in enhancing security measures within aviation facilities, thereby safeguarding personnel and assets. This conclusion has been consistently validated through sensitivity analyses conducted across diverse scenarios, wherein the weighting of benefits and challenges identified and categorized from literature was systematically varied. The proposed methodological approach is not limited to aviation but can be extended to various sectors seeking to leverage Digital Twins for operational optimization, sustainability enhancements, and gaining deeper insights into key performance indicators in diverse industries.

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1 Introduction

With rapid expansion of electric vehicles and aircraft in recent decades, there has been a notable increase in the exploitation of natural resources. This situation has led to the critical need of exploring new paths for resource reuse within the circular economy framework, so as to be able to optimize their useful life while reducing the exploitation of deposits (Baars et al. 2021). For this reason, many companies are increasingly embracing circularity-based economic models to optimize resource lifespan and minimize exploitation (Weigend Rodríguez et al. 2020).

Originating in the 1960s, this model emphasizes the sharing, borrowing, reusing, repairing, reconditioning, and recycling of materials and products to extend their lifecycle and reduce waste (Hobson et al. 2021). Once the product has completed its function, its composing materials are reintroduced, if possible through recycling. This practice enables us to reuse these components within the production cycle, ultimately generating further value. In order to successfully apply this model, not only should companies revolutionize their own logistics and production activities, but also they would need to be able to manage all the business processes that are part of the supply chain in a circular way. This is the reason why implementing new models would be appropriate to support companies in manage their activities in an integrated and more effective fashion.

With this regard, the concept of Digital Twin (DT) is gaining considerable diffusion. DTs offer comprehensive oversight of asset performance, facilitate proactive identification of potential failures, and enable informed maintenance and lifecycle decisions (Madni et al. 2019). Leveraging technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), and software analytics, DT-based models in manufacturing create real-time digital simulations, offering a powerful tool for optimizing operations. Global aviation contributes to climate change caused by aviation operations resulting from the burning of fossil fuels but is also responsible for other environmental problems caused by aircraft support systems such as fuel production, aircraft manufacturing and disposal, noise pollution, the poor use of metals or toxic impacts resulting from the release of chemicals that have the potential to cause harm to human health, ecosystems and the depletion of natural resources.

For this reason, we have selected the aviation sector as our research domain to address the issue concerning the implementation of DTs aimed at enhancing circular economy models. Our objective is to thoroughly analyze all factors contributing to the improvement of this sector, thus making it more sustainable. This approach could indeed represent the best solution to help managers in their production choices as it allows to achieve positive outcomes, for example: 1) tracking product and process data, as well as visualizing the operations and interactions between the digital and real components of the twin; 2) improving maintenance processes based on data received from sensors; 3) monitoring essential energy consumption to report operational efficiency and environmental sustainability; 4) mapping the flight of drones from real physical space to virtual space and comprehensively reflecting the flight environment and flight path, so as to have greater safety when drones are in airspace.

This paper aims to analyze the application of DTs within manufacturing companies, specifically focusing on the aviation industry's transition towards circular business models, particularly in the production and management of commercial aircraft fleets. By conducting a thorough analysis of the challenges and benefits associated with DT implementation, as well as evaluating the value generated by such integration, this paper proposes step-by-step decision-making model tailored to the aviation manufacturing sector for the adoption of circular operational models. Specifically, examining DT across various tiers in aviation, an integrated Multi-Criteria Decision-Making (MCDM) approach is developed to first determine the mutual importance of benefits and challenges that come into play, and to secondly prioritize the relevant parameters to be monitored by sensors for real-time data collection and monitoring of various components of aircraft and associated systems. Findings of research can be useful for companies in selecting key performance indicators (KPIs) that optimize the benefits of DT. With this regard, the proposed methodological framework aims to provide actionable insights for successful DT integration within the aviation manufacturing sector.

This document is organized through various sections. After introducing the research topic, Section 2 will provide a comprehensive literature review on DT's role in the circular economy and MCDM applications across various industrial sectors, aiming to identify the research gap. Section 3 will delineate the integrated MCDM methodology designed for addressing real-world challenges within the aviation industry, with a detailed case study presented in Section 4. Section 5 reports conclusions and future potential developments of this research.

2 Literature review

2.1 DT in the circular economy

To develop a comprehensive literature review regarding the impact of DTs on promoting circularity within corporate settings, it is essential to meticulously examine existing works of research concerning digital twins and their relevance to the circular economy. Since the first definition of a digital twin provided by the National Aeronautics and Space Administration (NASA) as a a virtual representation that serves as the real-time digital counterpart of a physical object or process, several authors have proposed their own integration according to specific application fields, in terms of a virtual or digital model (Martínez-Gutiérrez et al. 2023, Rosen et al. 2015). Various authors consider a DT as a Life Cycle Assessment (LCA) model, which means that a DT can be implemented throughout the entire life cycle, from cradle to grave, supporting in assessesing the complete environmental footprint of products. Grieves & Vickers (2017) suggest that DT technology can provide useful information on how to safely dispose a product and how to extract some by-products that can still be reused and introduced into the production cycle. Furthermore, after disposing the product, the data recorded by the DT can help design and implement an upgraded version of this product, embedded with more sophisticated features with respect to the previous generation. As DT-based technologies contribute to the creation of added value for companies, the circular economy has similarly had a great impact on both economic and environmental levels over the recent years, adopting a holistic approach with the creation of circular circuits of material flows, energy and waste which include all social activities (Masi et al. 2018). In order to generate a substantial advantage for companies, it is advisable to implement suitable circular models at a micro, meso and macro levels, promoting practices that include the 3R principle of Reuse, Reduction and Recycling of resources, aiming at decreasing environmental impact, increasing economic gain, protecting the environment and providing adequate consumption of resources (Gharfalkar et al. 2018). In the pursuit of augmenting the impact of eco-innovations and further advancing the circular economy, such scholars as Antikainen et al. (2018) and Neligan et al. (2023) suggest that digitalization can play a crucial part. They assert that digitalization not only holds the potential to enhance the effectiveness of these initiatives but also to foster the emergence of novel circular business models by enabling seamless information and data exchange. With this regard, De Jesus & Mendonça (2018) discuss about the importance of technical innovations for the design and production of high quality products, as well as for the development of more performing and circular business processes. Dantas et al. (2021) state that integrating the principles of circular economy in industry 4.0 technologies would offer enormous opportunities to improve sustainable practices and ultimately achieve sustainable development goals. These types of interactions would certainly enable the adoption of resource reduction practices along the entire supply chain, enabling the coordination of various activities among business companies working together as components of a larger ecosystem rather than single entities Mura et al. (2020). According to Antikainen et al. (2018), digitalization can contribute to improve the effective management of materials and maintenance, in other words the recorded data can provide useful indications about the wear state of materials, location and availability. In addition, the implementation of DTs can boost process efficiency and product durability while reducing waste and transaction costs. Substantial benefits may include encouraging the use of local suppliers and developing more virtuous production chains to streamline waste materials. The impacts of digitalization on sustainability can be categorized into two distinct levels: the direct environmental effects, associated with social and economic aspects, which are directly related to the production, transportation, usage, and disposal of digital technologies and devices; and the indirect environmental, social, or economic consequences stemming from alterations in products and production processes induced by the proliferation of digital technologies (Ma et al. 2024, Chen et al. 2020, Salvi et al. 2021). These effects can manifest when improvements in material or energy efficiency during the production of a product result in cost reductions. In turn, cost reductions can drive an increased demand for that product or related products and services, thereby partly or wholly counterbalancing the initial environmental benefits. Nevertheless, there is a scarcity of research investigating the mechanisms by which digital technologies can propel the circular economy forward, specifically by optimizing resource circulation within the supply chain (Wynn & Jones 2022). A study conducted by Burger et al. (2019) emphasizes that certain dimensions of the circular economy remain underexplored. Specifically, there is a conspicuous gap in our comprehension regarding how digitalization impacts the circular economy, particularly in the context of digital twin development.

2.2 Existing MCDM approaches

To evaluate whether the use of eco-innovation on circular models can be a strategically effective choice, it is appropriate to analyze several positive and negative aspects that may come into play. To such an aim, implementing structured approaches based on Multi-Criteria Decision-Making (MCDM) could be beneficial. These methods have been widely used for decades as effective tools capable of solving complex decision-making problems in various fields. Taherdoost & Madanchian (2023) provided a comprehensive overview of MCDM methods, their classification, and applications across different fields. Various MCDM techniques such as multi-objective methods, fuzzy-based approaches, data-driven models, and hybrid methodologies, their strengths, and limitations were analyzed by Sahoo & Goswami (2023). Amudha et al. (2021) highlighted the Fuzzy Technique for Order Preference by Similarities to Ideal Solution (TOPSIS) for handling uncertainty in decision-making processes. They presented the application of TOPSIS and other MCDM methods for effective decision-making. Let us explore the effectiveness of MCDM in complex decision-making across various industries.

In the renewable energy sector, researchers emphasized the significance of MCDM methods in technology selection and provided insights into approaches for enhancing their effectiveness in decision-making processes (Lak Kamari et al. 2020). Nasrollahi et al. (2023) applied MCDM techniques to prioritize Wave Energy Converters (WECs) for deployment in the Caspian Sea. They ranked potential alternatives and identified a suitable selection by integrating the Fuzzy Delphi method (FDM) with the Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE).

In the manufacturing industry, Ghaleb et al. (2020) focused on the selection of manufacturing processes using MCDM methods like TOPSIS, Analytic Hierarchy Process (AHP), and VIekriterijumsko KOmpromisno Rangiranje (VIKOR, Serbian acronym standing for multi-criteria optimization and compromise solution). Researchers proposed a methodology to evaluate the approaches based on multiple factors focusing on group decision-making. The selection of industrial robots in the automobile industry is challenging due to the ongoing development of robotic technology, and the introduction of unique features. Gamal & Mohamed (2023), addressed this by developing a Multi-Objective Optimization based on Ratio Analysis (MOORA) method to evaluate and rank five robots used in the automotive industry. The application of MCDM methods for machine selection in manufacturing by introducing a dual-MCDM approach was explored by Wang et al. (2023). Büyüközkan & Güler (2021) proposed a model using MCDM methods to evaluate Supply Chain Analytics (SCA) tools in the logistics industry. To rank the SCA tool alternatives, the researchers combined Hesitant Fuzzy Linguistic Term Set (HFLTS), AHP, Multi-Objective Optimization by Ratio Analysis, and the Full Multiplicative (MULTIMOORA).

In the aviation industry, Rasmussen et al. (2023) applied three MCDM methods - AHP, TOPSIS, and Simultaneous Evaluation of Criteria and Alternatives (SECA) to enhance supplier selection processes in the aerospace and defense industry. The researchers highlighted challenges in incorporating such criteria as sustainability and technology while maintaining standard processes in the industry. Markatos & Pantelakis (2023) applied

MCDM methods to assess and compare commercial aircraft based on sustainability criteria. They proposed a methodology combining AHP and a weighted addition model to support decision-making in aircraft selection. Bhadra & Dhar (2022) used MCDM methods to select the best natural fiber for use in Natural Fiber-Reinforced Polymer (NFRP) composites for aerospace cabin interiors. They compared twelve alternatives using Fuzzy Integrated AHP, TOPSIS, Evaluation Based on Distance from Average Solution (EDAS), and Complex Proportional Assessment (COPRAS) methods for optimal NFRP composites. Maity et al. (2023) implemented MCDM techniques to select the optimal material for the wing structure of flying robots. They compared materials based on their physical and mechanical properties and concluded that carbon fiber could be considered the best material for Unmanned Aerial Vehicle (UAV) design and development. AliFarsi (2023) proposed a framework for optimizing maintenance and inspection for Unmanned Aircraft Systems (UAS) using MCDM. He addressed the complexities of UAS maintenance due to multiple subsystems and failure models and proposed a solution based on Reliability-based Maintenance (RBM-MCDM) and Fuzzy set theory. The framework improved system reliability and availability while considering maintenance costs and dynamic planning situations.

2.3 Research gap

Many researchers focused on the implementation of DTs in the aviation industry. Xiong & Wang (2022) explored the potential of DT technology by highlighting the primary application areas of DT in aviation and its significance in manufacturing and maintenance. A comprehensive IoT-enabled modular architecture for predictive maintenance in aircraft was developed by Bisanti et al. (2023). This study presents a comprehensive analysis of twenty-six key research papers on DT in aerospace maintenance. It examines different modeling approaches, identifying the aircraft subsystems involved in DT technology, and presenting a modular framework for predictive maintenance. The framework addresses ongoing research challenges in areas such as Big Data, IoT, and Deep Neural Networks. An intelligent predictive maintenance method for aero-engines driven by DT was developed by Xiong et al. (2021). The researchers generated health factors using the Implicit Digital Twin (IDT) model, applied to evaluate and monitor the degradation process of the aero-engine throughout its lifecycle. By the application of the deep learning approach Long Short-Term Memory (LSTM), the remaining life of the aero-engine was predicted. Furthermore, a few researchers worked on specific processes or sections related to the aviation industry and the related implementation of DTs. For instance, in order to improve Maintenance, Repair, and Operations (MRO), Apostolidis & Stamoulis (2021) optimized the placement of sensors within a Power Electronics Cooling System (PECS) of a modern airliner to enhance input data quality for an AI-based DT. Kilic et al. (2023) enhanced flight safety and operational efficiency using machine-learning techniques by estimating Electronic Centralized Aircraft Monitoring (ECAM) parameters for a wide-body commercial aircraft with a triple-spool turbofan engine. The DTs were used by Xu et al. (2021) to optimize the gas exchange system of a 2-stroke heavy-fuel aircraft engine, improving manufacturing efficiency and performance through virtual simulation and real-time feedback.

In the area of achieving sustainability or circularity in the aviation industry, very little research was carried out. Dias et al. (2022) presented the possibilities for applying a circular economy in the aerospace industry. The research contributes by identifying and analyzing CE-related practices applicable to aerospace, evaluating these practices in three global aerospace companies, and proposing a guidance framework for CE implementation in the industry. However, limitations include a lack of extensive theoretical review beyond the aerospace sector and a small sample size of companies studied. A systematic approach for evaluating material selection in aviation sustainability, considering the implementation of alternative fuels and circular economy principles was developed by Markatos & Pantelakis (2022a), The research introduces circular economy indicators in material selection considering ecological, economic, and circularity aspects, although these indicators provide valuable insights but they require complementation with life cycle assessment (LCA) data to ensure comprehensive sustainability and circularity assessments This study underscores the need for standardized procedures to enhance the validity and transparency of such assessments and suggests future research directions, including extending the tool's application to aircraft subsystem levels and addressing barriers to the use of recycled materials in aviation, particularly for high-performance components. Markatos & Pantelakis (2022b) evaluated how recycled carbon fiber reinforced plastic (CFRP) components contribute to circularity in aviation, particularly for hydrogen-fueled aircraft, using a material selection tool.

However, to the best of the authors' knowledge, a comprehensive MCDM framework focusing on DT implementation in the aviation industry, particularly within the context of sustainability and the adoption of a circular economy model, has not been previously developed. To address this research gap, our paper undertakes a detailed examination of DT implementation across various tiers within the aviation industry. It aims to identify the significant challenges and benefits associated with this implementation while also developing an integrated MCDM model tailored specifically for manufacturing companies looking to embrace circular models in their operations. This decision-making model will assist companies in selecting the most crucial indicators that maximize the benefits derived from DT integration.

3 Materials and methods

The proposed methodology develops of the following three main stages, graphically synthetized in Figure 1.

- Analysing relevant benefits and barriers for DT implementation in the aviation sector. In this initial step, our analysis will focus on the prominent benefits and challenges highlighted in a previous study (Pattan et al. 2024), which was conducted on the basis of a thorough literature review. By synthesizing the key findings of this study, we lay the foundational basis for this research, supporting stakeholders in developing a comprehensive understanding of the numerous opportunities and barriers linked to the implementation of DT within the aviation sector. This approach ensures that the analysis is grounded in empirical evidence and informed by the collective knowledge of the field.

- Weighting benefits and barriers by involving experts opinions and implementing the Fuzzy DEcision MAking Trial and Evaluation Laboratory (Fuzzy DEMATEL). After identifying the benefits and barriers, the next step consists in assigning weights to each factor. This is achieved through expert input and collaboration to determine the relative significance of each factor in the context of DT implementation in aviation. Additionally, the Fuzzy DEMATEL method is herein proposed to refine the weighting process. With respect to other MCDM techniques, the Fuzzy DEMATEL captures the interdependencies and relationships between different factors, allowing for a nuanced assessment of their importance in DT implementation and effectively prioritizing them for successful DT implementation in aviation.

- Ranking relevant parameters associated to sensors to be installed by maximizing benefits and minimizing barriers of implementation in the context of circular economy. With the weighted benefits and barriers in mind, the focus shifts to selecting and prioritizing parameters associated with sensors for installation within the aviation sector, particularly to align with circular economy principles. These parameters undergo ranking based on their potential to maximize benefits and minimize barriers associated with DT implementation, using the TOPSIS methodology. TOPSIS provides a comprehensive assessment, prioritizing parameters that support circular economy objectives, ensuring sustainable sensor installation while mitigating DT-related challenges in aviation operations. By implementing the final ranking via TOPSIS, stakeholders can make informed decisions by considering multiple factors simultaneously, thus identifying the most suitable parameters for sensor deployment within the circular economy framework.

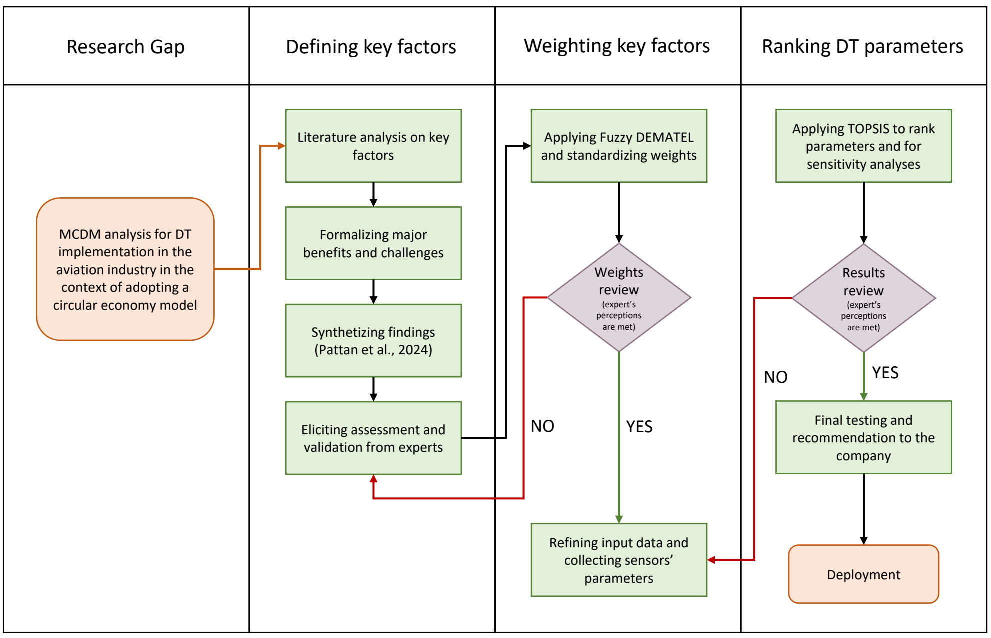

Fig. 1. Methodological framework

3.1 Defining key factors

A comprehensive analysis of recently published research papers was developed in a previous conference contribution (Pattan et al. 2024), with the aim of investigating the most significant challenges and benefits of DT implementation within the aviation industry. The findings are summarized in Tables 1, offering a comprehensive overview of the primary insights collected from the current literature.

Table 1. Literature analysis on major challenges and benefits in DT implementation

ID	Challenge	Ref.	ID	Benefit	Ref.
C_1	Uncertainty in creating an actual environment or scenario	Jyeniskhan et al. (2023)	B_1	Enhanced Predictive Maintenance	Mohsen & Gokhan (2023)
C_2	Difficulty in predicting safety levels for performance optimization	Perno et al. (2022)	B_2	Safety enhancement	Rasheed et al. (2020)
C_3	Unreliability of real-time input data	Jyeniskhan et al. (2023)	**B_3**	**Improved productivity and efficiency**	Soori et al. (2023)
C_4	Challenges in implementing complex supply chain processes	Singh et al. (2018)	**B_4**	**Enhanced quality control**	Soori et al. (2023)
C_5	Complexity of risk assessment requirements for DT implementation	Millwater et al. (2019)	**B_5**	**Reduced production cost**	Soori et al. (2023)
C_6	Cyber security issues	Rasheed et al. (2020)	**B_6**	**Efficient supply chain**	Sharma et al. (2022)
C_7	**Complexity of compatible structure**	Jyeniskhan et al. (2023)	B_7	Increased Cross-functional collaboration	Mohsen & Gokhan (2023)
C_8	**Precision and accuracy related challenges**	Rasheed et al. (2020)	B_8	Increased operational efficiency	Mohsen & Gokhan (2023)
C_9	**Data management and processing related challenges**	Jyeniskhan et al. (2023)	B_9	Improved product development	Botín-Sanabria et al. (2022)
C_{10}	Data security related challenges	Jyeniskhan et al. (2023)	B_{10}	Optimized product life cycle	Sharma et al. (2022)
C_{11}	Model related issues	Jyeniskhan et al. (2023) and Sharma et al. (2022)	B_{11}	Improved decision support system	Rasheed et al. (2020)
C_{12}	Complications in integrating system and IT infrastructure	Jyeniskhan et al. (2023) and Attaran & Celik (2023)	B_{12}	Enchanced personalization of products and services	Rasheed et al. (2020)
C_{13}	Large-scale computation	Rasheed et al. (2020) and Van-DerHorn & Mahadevan (2021)	**B_{13}**	**Smart production network**	Lu et al. (2020)
C_{14}	**Lack of standards, frameworks, and regulations**	Botín-Sanabria et al. (2022)	B_{14}	Improved customer satisfaction	Mohsen & Gokhan (2023)

The factors highlighted in bold in Table 1 have been identified as exerting a significant impact on other factors according to (Pattan et al. 2024). We specifically concentrate on these key factors, which serve as criteria for the integrated MCDM application, whose methodological details are reported in the next subsections. We specify as, in the preliminary stage of application, experts from the aviation industry will be engaged to conduct pairwise comparisons of the key factors. Through this process, they will establish the degree of influence one parameter holds over another. This stage lays the foundation for subsequent decision-making processes in DT implementation. After collecting and aggregating experts' judgments (see the first two points of next subsection 3.2), the key factors will be weighted via the Fuzzy DEMATEL. Subsequently, the calculated weights will be used as input data for the final ranking of sensor parameters. The ultimate objective is to determine the parameters that should be prioritized for monitoring within the context of circular economy implementation in the aviation industry, aiming to maximize benefits while minimizing challenges associated with DT implementation.

3.2 Weighting key factors

Broadly speaking, Fuzzy DEMATEL facilitates a comprehensive and actionable assessment of DT implementation's impact, empowering stakeholders to optimize strategies for maximizing benefits and addressing challenges within the circular economy paradigm. The choice of including this approach in our methodological framework refers to various reasons, supported by the existing literature. Firstly, as previously mentioned, Fuzzy DEMATEL adeptly manages inherent uncertainty in subjective stakeholder opinions (Yu et al. 2023), providing a nuanced understanding of perceptions regarding factor relationships (Rivas Pellicer et al. 2023, Feldmann et al. 2022). Secondly, it efficiently discerns the components comprising the cause-and-effect chain of a complex system (Zhao, Hendalianpour & Liu 2024), offering a holistic view of their influences within the aviation ecosystem. Lastly, Fuzzy DEMATEL quantifies and ranks the strength of these influences (Ahmadi et al. 2023), enabling decision-makers to prioritize resources effectively based on the relative importance of factors.

On the basis of these reasons, the Fuzzy DEMATEL application is herein proposed to weight benefits and challenges on the basis of their (standardized) prominence values. In this procedure, a decision-making group of K experts is first composed to carry out the evaluation process. A comprehensive methodological description is detailed next (Carpitella et al. 2023).

- Collection of pairwise comparison matrices of input from the decision-making team. Each expert is asked to assign linguistic evaluations with relation to pairs of criteria, expressing the strength of the relationship of one factor over another one. The elicited evaluations are collected in pairwise comparison matrices (one for each expert), and then translated to Triangular Fuzzy Numbers (TFN), $\tilde{z} = (l, m, u), l \leq m \leq u \in [0, 1]$. We assume the triplet $(0, 0, 0.25)$ as denoting no interaction (NO); $(0, 0.25, 0.5)$ as referring to very low interaction (VL); $(0.25, 0.5, 0.75)$ as a low interaction (L); $(0.5, 0.75, 1)$ as a high interaction (H); and $(0.75, 1, 1)$ as representing very high interaction (VH).

- Conversion of pairwise comparison matrices into Fuzzy Direct-Relation (FDR) matrices and executing an aggregation process. Pairwise comparison matrices elicited by the involved experts are then translated to FDR matrices, in which each cell contains a TFN on the basis of the scale defined above. Specifically, the generic fuzzy matrix $\tilde{Z}^{(k)}$ reporting the input FDR matrix, elicited by k^{th} expert, can be expressed as:

$$\tilde{Z}^{(k)} = \begin{bmatrix} (0,0,0) & \tilde{z}_{12}^{(k)} & \dots & \tilde{z}_{1n}^{(k)} \\ \tilde{z}_{21}^{(k)} & (0,0,0) & \dots & \tilde{z}_{2n}^{(k)} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{z}_{n1}^{(k)} & \tilde{z}_{n2}^{(k)} & \dots & (0,0,0) \end{bmatrix}, k = 1, 2, \dots, K; \tag{1}$$

where $\tilde{z}_{ij}^{(k)} = (l_{ij}^{(k)}, m_{ij}^{(k)}, u_{ij}^{(k)})$, K is the number of decision-makers, and $\tilde{z}_{ii}^{(k)} = (0, 0, 0)$ for $(i = 1, 2, \dots, n)$. The matrices are subsequently aggregated by performing the weighted mean in order to take into account the (potential) different degrees of expertise of the decision-makers composing the team. The resulting aggregated FDR matrix is denoted as $\tilde{Z}$.

- Normalization of the fuzzy direct-relation matrix. This operation is performed by manipulating each of the elements of matrix $\tilde{Z}$ as:

$$\tilde{x}_{ij} = \frac{\tilde{z}_{ij}}{r} = \left(\frac{l_{ij}}{r}, \frac{m_{ij}}{r}, \frac{u_{ij}}{r}\right), \tag{2}$$

where

$$r = \max_{ij}\left\{\max_i \sum_{j=1}^{n} u_{ij}, \max_j \sum_{i=1}^{n} u_{ij}\right\}, 1 \leq i, j \leq n. \tag{3}$$

Let us denote the normalized FDR matrix $\tilde{X}$.

- Computation of the fuzzy total-relation matrix. In the traditional version of (crisp) DEMATEL, the total-relation matrix T associated to the normalized (crisp) matrix X is achieved as follows:

$$T = \lim_{w\to\infty}(X + X^2 + \ldots + X^w) = X(I - X)^{-1}, \tag{4}$$

where I denotes the identity matrix. The applied normalization ensures the convergence of this series. In the fuzzy version of DEMATEL, the calculation of the total-relation matrix is made element-wise for the components of the TFNs in the FDR matrix by using the binary operator $\oplus$:

$$\tilde{T} = \lim_{w\to\infty}(\tilde{X} \oplus \tilde{X}^2 \oplus \ldots \oplus \tilde{X}^w) \tag{5}$$

Once again, the normalization ensures the convergence of the three series involved (2). Referring to the matrices of the first (lower), second (medium), and third (upper) components of the TFNs within X as X_l, X_m, and X_u respectively, the elements of matrix $\tilde{T}$ can be formulated as $\tilde{t}_{ij} = (l^*_{ij}, m^*_{ij}, u^*_{ij})$, with:

$$[l^*_{ij}] = X_l(I - X_l)^{-1}; \tag{6}$$

$$[m^*_{ij}] = X_m(I - X_m)^{-1}; \tag{7}$$

$$[u^*_{ij}] = X_u(I - X_u)^{-1}. \tag{8}$$

- Computation of the crisp total-relation matrix. The fuzzy numbers in $\tilde{T}$ are now converted into crisp values. The Converting Fuzzy Data into Crisp Scores (CFSC) algorithm suggested by Opricovic & Tzeng (2003) is herein proposed as defuzzification technique to obtain the crisp total-relation matrix T. A suitable threshold, calculated as the mean of all the values in matrix T, will be used to avoid to take into account negligible relations.

- Production of the causal relationship diagram. The final chart is derived from matrix T, after excluding values below the specified threshold. Specifically, we first perform the sums of its rows (D) and its columns (R), and we then calculate the quantities $(D + R)$ and $(D - R)$. The sum $(D + R)$, also referred to as prominence, represents the global significance of element i within the system. The difference $(D - R)$, referred to as relation, quantifies its net impact due to component i. The causal relationship diagram is achieved by plotting $(D + R)$ on the horizontal axis and $(D - R)$ on the vertical axis and mapping each of the factors accordingly.

The prominence values obtained from Fuzzy DEMATEL will be prepared for subsequent use as weights in the TOPSIS method. To such an aim, a standardization process is undertaken. This consists in transforming the prominence values into a uniform scale to ensure comparability across criteria. Initially, the values are normalized by dividing each prominence value by the sum of all prominence values, ensuring they fall within a consistent range. Once standardized, these values are directly utilized as weights in the TOPSIS method, representing the relative importance of each criterion in the decision-making process. This allows stakeholders to systematically evaluate alternatives based on criteria importance, facilitating informed decision-making regarding DT implementation.

It is useful to specify that, following standardization, the obtained weights will be reviewed by the involved experts to ensure consensus. If experts collectively agree on the weights, they will be considered as definitive for the next and last stage of our methodological framework. However, in the case in which consensus is not reached, experts will be invited to provide new evaluations. Subsequently, the Fuzzy DEMATEL procedure will be reinitialized to recalibrate the weights based on the updated assessments. This iterative approach ensures that the final weights accurately reflect the collective expertise and insights of the panel of experts, thereby enhancing the reliability and robustness of the decision-making process.

3.3 Ranking DT parameters

TOPSIS is widely recognized as a MCDM technique capable to empower decision-makers to make informed, data-driven decisions by achieving a prioritized ranking of alternatives under different evaluation criteria. In the context of our research, a final ranking of parameters related to sensors for DT implementation in aviation industry within the circular economy framework can be effectively achieved by employing a TOPSIS-based perspective. TOPSIS allows for a comprehensive evaluation by considering a plethora of criteria, ensuring a balanced assessment across multiple aspects (Carpitella et al. 2019). Its structured framework handles the complexity inherent in complex engineering fields, streamlining process and facilitating stakeholder consensus (Elkady et al. 2024). TOPSIS enables quantitative analysis and sensitivity evaluation (Yang & Chen 2023), providing an effective basis for evaluating the robustness of final results (Fu et al. 2023). Because of these evidences, the TOPSIS method is herein proposed to enable a comprehensive assessment of parameters related to DT sensors while considering both benefits and barriers associated with DT implementation. Particularly, this technique is herein suggested to rank parameters by assuming as criteria the factors previously weighted through the Fuzzy DEMATEL. The procedural steps necessary to carry out the TOPSIS method are outlined.

- Creation of the input assessment matrix. This is done on the basis of quantitative evaluations g_{ij} collected for each alternative i under each criterion j.
- Computation of the normalized matrix. In such a matrix, the generic element z_{ij} represents the normalized evaluation of alternative i under criterion j, something that can be written as:

$$z_{ij} = \frac{g_{ij}}{\sqrt{\sum_{i=1}^{n} g_{ij}^2}}. \tag{9}$$

- Calculation of the weighted and normalized matrix, in which the generic element u_{ij} is determined as follows:

$$u_{ij} = w_j \times z_{ij}, \forall i, \forall j; \tag{10}$$

  w_j denoting the weight of criterion j, as assigned to characterize its mutual importance within the whole set of evaluation criteria.

- Computation of the positive and negative ideal solutions, denoted as A^* and A^-, respectively. The following equations are used to such an aim:

$$A^* = (u_1^*, \ldots, u_k^*) = \{(\max_i u_{ij} | j \in I^{'}), (\min_i u_{ij} | j \in I^{''})\}; \tag{11}$$

$$A^- = (u_1^-, \ldots, u_k^-) = \{(\min_i u_{ij} | j \in I^{'}), (\max_i u_{ij} | j \in I^{''})\}; \tag{12}$$

  $I^{'}$ and $I^{''}$ representing the sets of criteria to be respectively maximized and minimized.

- Calculation of the geometric distances from each alternative i to the positive ideal solution A^* and the negative ideal solution A^-. These distances are respectively denoted as S^* and S^-, and calculated by applying the following formulas:

$$S^* = \sqrt{\sum_{j=1}^{k} (u_{ij} - u_{ij}^*)^2}, i = 1, \ldots, n; \tag{13}$$

$$S^- = \sqrt{\sum_{j=1}^{k} (u_{ij} - u_{ij}^-)^2}, i = 1, \ldots, n. \tag{14}$$

- Determination of the closeness coefficient C_i^* for each alternative i. This coefficient indicates how well each alternative performs with relation to the two ideal solutions, and is obtained as follows:

$$C_i^* = \frac{S^-}{S^- + S^*}, 0 < C_i^* < 1, \forall i. \tag{15}$$

- Formalization of the final ranking of alternatives. The ranking is established by arranging alternatives according to their decreasing associated values of closeness coefficients. For example, when comparing two generic alternatives i and z, if $C_i^* \geq C_z^*$, then alternative i has to be preferred over alternative z.

After obtaining the final results via TOPSIS, they will be once again subjected to review by experts to assess their practical significance. This review aims to ensure that the ranking derived from TOPSIS accurately reflect the real-world implications and considerations of DT sensor parameter selection in the aviation industry within the circular economy context. Additionally, sensitivity analysis of criteria weights will be conducted to generate multiple rankings, allowing decision-makers to confirm the robustness of the results.

If the outcomes of the sensitivity analysis prove to be significant, they will be formalized into managerial recommendations. These recommendations will be conveyed to the company responsible for the deployment stage of DT implementation in aviation, guiding them in making informed decisions regarding the selection and deployment of sensor parameters. This iterative process ensures that the final recommendations are grounded in practicality and effectively address the objectives and challenges of DT implementation in the aviation industry.

4 Case study in the aviation sector

The present case study focuses on operational aspects of the aviation sector, with the goal of providing a roadmap for prioritizing sensors installation throughout DT implementation. Specifically, we are going to apply the previously described methodological framework to first weight relevant criterai (i.e., benefits and challenges) via the Fuzzy DEMATEL, and to secondly prioritize alternatives (i.e., types of sensors to be installed) via TOPSIS on the basis of: 1) the technical parameters they can effectively monitor, and 2) the specific benefits and challenges that can be respectively maximized and addressed by employing those specific sensor types. We will lastly evaluate the robustness of final results by implementing a thorough sensitivity analysis on criteria weights.

4.1 Application on defining key factors

Table 1 reports a comprehensive literature review analyzing several benefits and challenges related to DT implementation in the aviation sector within the circular economy framework (Pattan et al. 2024). In the present case study, we specifically focus on a subset of nine key factors or criteria, that are the five benefits and four challenges highlighted in bold in Table 1, namely:

- 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_{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));

- 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_{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)).

As specified before, the choice of this subset of nine criteria emerges from our previous study (Pattan et al. 2024), where we had comprehensively evaluated all the benefits and challenges herein reported in Table 1 and applied a structured approach to select the most relevant ones.

We are herein proceeding by further screening the identified subset of criteria with the support of a decision-making team. The team includes three experts from different background, each one of them with relevant industrial experience. We specify that we have been carefully selected each expert on the basis of the value expected to be added through their contribution to the decision-making process, so as to bring a variety of experiences, knowledge, and diverse perspectives in the formalization of final results.

All of the three selected experts possess relevant knowledge and expertise in the subject matter object of the present research. Specifically, the involved decision-making team consists of a Senior Operations Manager with a deep understanding of optimization (Expert 1), a Supply Chain Director with a proved efficiency oriented vision (Expert 2), and a Production Manager as a specialist in streamlining core processes within the aviation industry (Expert 3).

Several brainstorming sessions were led together with the experts, during which we asked to pairwise compare criteria and provide linguistic evaluations of influence by using the scale reported at the second point of subsection 3.2. Experts have been equally weighted (weight = $1/3$). This means that each expert's opinion or input is considered equally valuable or significant in the decision-making process. Regardless of their specific roles or expertise, their viewpoints carry the same level of importance and are given equal consideration when making decisions. This approach is useful when dealing with a diverse team with members possessing different areas of expertise, as it is in our case, to ensure fair and balanced consideration of their perspectives.

Once collected judgments elicited by each expert, we aggregated them into a single matrix, graphically displayed in Figure 2. It can be observed as the arrays of the mentioned nine criteria (benefits and challenges), numbered from 0 to 8, are reported in the rows and the columns of each matrix of Figure 2. Furthermore, we can observe distinct patterns across experts' perspectives. Color-coding indicates different degrees of influence intensity levels, ranging from "No Influence" (darker color) to "Very High Influence" (lighter color). For example, we can visualize as, with respect to Experts 1 and 3, Expert 2 tends to assign lower levels of influence when pairwise comparing criteria.

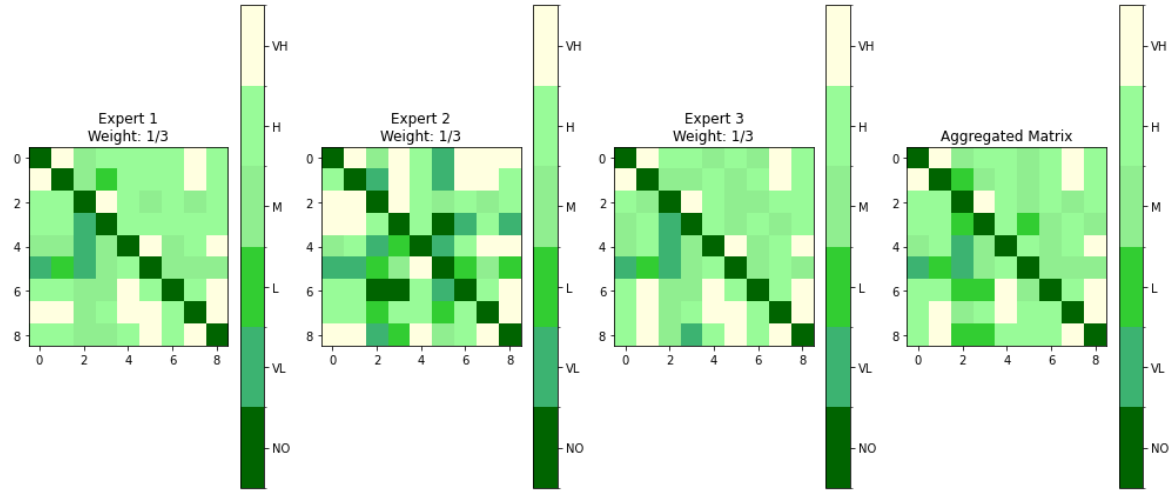

Fig. 2. Judgments of influence provided by experts individually and aggregated matrix

We can also notice as matrices produced by Expert 1 and Expert 3 look similar, but it is worth to mention that some evaluations are quite different, spanning from "Medium Influence" to "Very High Influence".

While each expert produced a personal matrix, being linguistic evaluations of influence subjective, the aggregate matrix merges the provided opinions as if the team was composed by a single decision maker. This aims to increase the objectivity of the decision-making process while taking into account expert experience. The aggregated matrix reflects indeed a blend of individual expert opinions and exhibits several significant characteristics. Notably, the intensities of the colors are averaged, with fewer dark colors compared to the individual matrices. This is justified by the fact that all of the three experts have been attributed the same weight.

4.2 Application on weighting key factors

The aggregated matrix reported in Figure 2 is considered as the input matrix for the Fuzzy DEMATEL application. Calculations have been performed in Python. Table 2 reports the matrix of (absolute) crisp values T obtained by iterating the Fuzzy DEMATEL procedure. Table 3 shows Prominence $(D + R)$ and Relation $(D - R)$ values computed for each criterion from matrix T.

Higher prominence values are associated to those parameters with higher degree of interconnection with all the other parameters, then with higher influence on the whole system. Relation values serve to categorize criteria as causes $(D - R > 0)$, when they influence other parameters, or effects $(D - R < 0)$, when they are mostly influenced by other parameters.

Results are synthesized in Figure 3, from which we can prioritize criteria on the basis of their prominence values, by reading the graph from the right to the left.

For instance, we can observe as B_{13} (smart production network), B_3 (improved productivity and efficiency), C_9

Table 2. The matrix of (absolute) crisp values T

ID	Benefits B_3	B_4	B_5	B_6	B_{13}	Challenges C_7	C_8	C_9	C_{14}
B_3	0.2650	0.3200	0.3000	0.3570	0.3710	0.2380	0.3260	0.3510	0.1720
B_4	0.3580	0.2300	0.2640	0.3550	0.3430	0.2370	0.3130	0.3370	0.1660
B_5	0.2150	0.1980	0.1280	0.2630	0.2350	0.1840	0.1530	0.1830	0.0890
B_6	0.3300	0.2720	0.2570	0.2340	0.3230	0.2230	0.2620	0.2960	0.1160
B_{13}	0.3810	0.3350	0.3050	0.3810	0.2900	0.3010	0.3430	0.3690	0.1900
C_7	0.2920	0.2700	0.2340	0.3200	0.3130	0.1790	0.2930	0.3170	0.1480
C_8	0.3670	0.3330	0.2820	0.3580	0.3870	0.3090	0.2560	0.3750	0.2080
C_9	0.3450	0.3270	0.2610	0.3500	0.3710	0.2700	0.3350	0.2590	0.1730
C_{14}	0.3510	0.3180	0.2730	0.3570	0.3410	0.3170	0.3350	0.3450	0.1320

Table 3. Prominence (D+R) and Relation (D-R) values

ID	D	R	$D+R$	$D-R$	Weights
B_3	2.7001	2.9046	5.6050	-0.2050	0.1226
B_4	2.6032	2.6039	5.2070	-0.0010	0.1139
B_5	1.6482	2.3042	3.9520	-0.6560	0.0864
B_6	2.3128	2.9740	5.2870	-0.6610	0.1156
B_{13}	2.8959	2.9756	5.8720	-0.0800	0.1284
C_7	2.3667	2.2585	4.6250	0.1080	0.1011
C_8	2.8774	2.6167	5.4940	0.2610	0.1201
C_9	2.6903	2.8325	5.5230	-0.1420	0.1208
C_{14}	2.7706	1.3952	4.1660	1.3750	0.0911

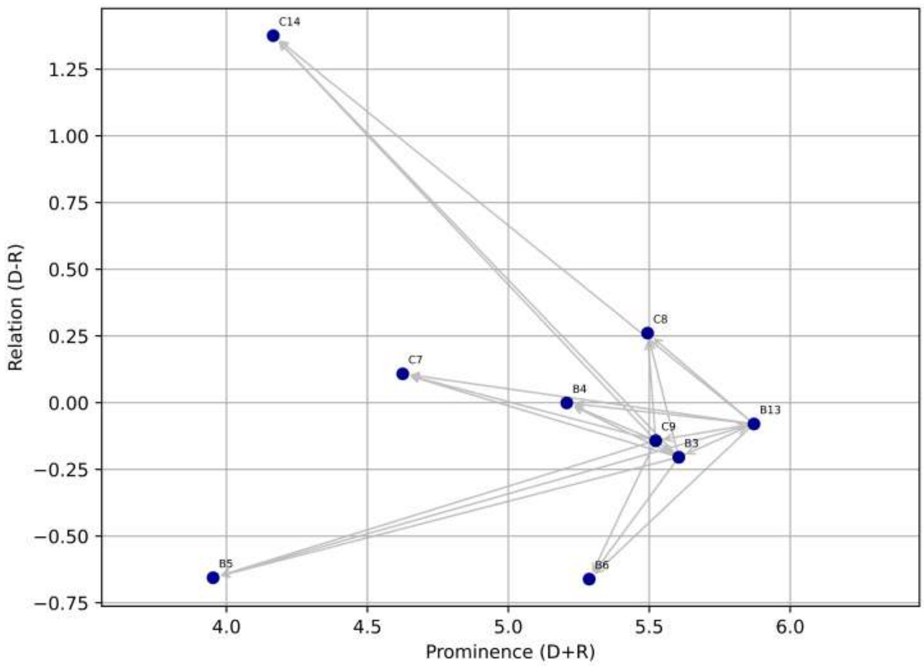

Fig. 3. Interdependence Graph

(data management and processing related challenges), and C_8 (precision and accuracy related challenges) are, in order, the most prominent aspects according to the evaluations provided by the involved group of experts.

Moreover, on the one hand, B_{13} and B_3 are categorized as effects, representing the positive outcomes of implementing smart production networks, enhancing productivity, and optimizing supply chains. On the other hand, C_8 is identified as a cause, highlighting challenges in precision and accuracy that may impact efficiency, while C_9 is considered an effect, indicating challenges arising from data management issues.

The values of prominence $(D + R)$ associated to factors reported in Table 3 have been normalized and will be used as criteria weights (last column of Table 3) for ranking DT parameters as reported in the following subsection.

4.3 Application on ranking DT parameters

When planning to implement a DT, it is essential to rank sensors based on the parameters they monitor. This prioritization enables the formulation of efficient monitoring strategies while ensuring efficient utilization of resources within the DT system. This focused approach aims to enhance data quality by emphasizing critical parameters, improving the accuracy and reliability of insights and predictions generated by the DT. Additionally, prioritizing sensors aids in risk identification and mitigation, particularly concerning safety, compliance, or operational issues. By closely monitoring critical parameters, potential adverse events or non-compliance can be proactively addressed. It is also clear as ranking sensors fosters adaptability and scalability in our application field. As the system evolves, decisions regarding sensor upgrades or additions can be swiftly and effectively implemented to meet evolving requirements, ensuring the DT remains aligned with operational needs.

Table 4 synthesizes several types of sensors that have been recognized in literature as useful within the domain of research of the present paper. We provide a synthetic description by specifying which parameters they can effectively monitor and which benefit/challenge they can maximize/address in the most effective way. The list reported in Table 4 is considered as the set of alternatives to be ranked in the following TOPSIS application.

Table 4. Sensors and monitored parameters related to main benefits and challenges (Table 1)

ID	Sensor Types	Description	Ref.
P_1	Laser distance sensors	They provide precise distance measurements, ideal for critical applications like aligning machinery and monitoring product dimensions. They can effectively address challenges C_8 (precision and accuracy-related).	Poole et al. (2022)
P_2	Optical encoders	They offer precise position feedback, converting motion into digital signals, and are widely used for accurate positioning and movement control. They can effectively address challenges C_8 (precision and accuracy-related).	Zhao, Ban, Zhang, Shi, Chen & Liu (2024)
P_3	IoT sensors	They gather such manufacturing data as temperature, pressure, and vibration, for optimizing efficiency, predictive maintenance, and enhancing performance. They can be used to overcome the challenge C_9 (data management and processing related).	Rodrigues et al. (2022)

Continued on next page

Table 4 – Continued from previous page

ID	Sensor Types	Description	Ref.
P_4	Data loggers	They capture and store time-based data, such as temperature, humidity, and voltage, helping in monitoring manufacturing conditions, equipment performance, and process parameters for improved quality control and optimization. Challenge C_9 (data management and processing related) can be overcome by this type of sensors.	Jedermann et al. (2023)
P_5	Compliance sensors	They monitor environmental conditions for industry regulation adherence, including air quality in manufacturing or hazardous material tracking. This can serve as a solution to address the challenge C_7 (complexity of compatible structure).	Shiryayev et al. (2022)
P_6	Barcode/QR code scanners	They help in product identification, traceability, and regulatory compliance by enabling accurate tracking throughout the supply chain. They can effectively address the challenge C_7 (complexity of compatible structure).	Udoy et al. (2023)
P_7	Proximity sensors	They detect the presence or absence of objects without physical contact. They simplify equipment design by replacing mechanical switches and enabling compatibility with various materials and structures. They can serve as a solution for challenge C_{14} (lack of standards, frameworks, and regulations).	Moheimani et al. (2022)
P_8	Wireless sensors	They eliminate the need for complex wiring and infrastructure, offering flexibility and ease of integration into existing manufacturing systems. They can minimize the complications associated with challenge C_{14} (lack of standards, frameworks, and regulations).	Han et al. (2022)
P_9	GPS tracker	They provide real-time location data for tracking shipments and inventory throughout the supply chain, by enabling efficient route planning, reducing transit times, minimizing the risk of lost or stolen goods, and optimizing supply chain logistics. They can increase the effectiveness of the benefit B_6 (efficient supply chain).	Keates (2023)
P_{10}	RFID temperature sensors	They track perishable goods' temperature in transit, ensuring optimal conditions and maintaining product quality. This can enhance the benefit B_6 (efficient supply chain).	Suresh & Chakaravarthi (2022)
P_{11}	Ultrasonic level sensors	They measure liquid/solid levels in tanks using ultrasonic waves, optimizing material usage and reducing waste. This type of sensor can relate to and enhance the benefit B_5 (reduced production cost).	Bowler et al. (2022)
P_{12}	Energy consumption sensors	They monitor electricity, gas, and water usage in manufacturing to reduce costs and enhance sustainability. They can add value to the advantages related to the benefit B_5 (reduced production cost).	Pham et al. (2022)
P_{13}	Vision inspection systems	They use cameras and algorithms for real-time quality control, detecting defects, and ensuring product consistency. This can significantly enhance the effectiveness of benefit B_4 (enhanced quality control).	Stojadinovic et al. (2022)

Continued on next page

Table 4 – Continued from previous page

ID	Sensor Types	Description	Ref.
P_{14}	Force/Torque sensors	These sensors measure applied force or torque during manufacturing, ensuring proper assembly and preventing damage. They can maximize the advantages of benefit B_4 (enhanced quality control).	Yingjun et al. (2024)
P_{15}	Wireless vibration sensors	They monitor the vibration levels of machinery and equipment in real time. By detecting abnormal vibrations or faults early, these sensors help in preventing equipment failures, minimize downtime, and optimize maintenance schedules. Deploying this type of sensor can optimize the effectiveness of benefit B_{13} (smart production network).	Wang et al. (2024)
P_{16}	Smart pressure sensors	They measure fluid or gas pressure in manufacturing processes and equipment, providing valuable data for process optimization, and predictive maintenance, and ensuring safety and efficiency. They maximize the effectiveness of benefit B_{13} (smart production network).	Szczerba et al. (2022)
P_{17}	Motion sensors	By automating machinery and triggering processes in manufacturing, they optimize workflow activating equipment upon detection and reducing cycle times. This type of sensors significantly strengthens the effectiveness of benefit B_3 (improved productivity and efficiency).	Asad et al. (2023)
P_{18}	Ambient light sensors	They gauge light intensity in manufacturing environments, adjusting lighting based on natural light, occupancy, and time of day. This optimization promotes comfortable, productive workspace while reducing energy use and costs. These sensors contribute to the advantages associated with benefit B_3 (improved productivity and efficiency).	Wawrzyński et al. (2022)

Alternatives have been evaluated with the support of the same team of experts by using a 5-point scale.

Table 5. Evaluations of alternatives under benefits and challenges, Closeness Coefficients and ranking positions

Criteria ID/Weights	**B_3 0.1226**	**B_4 0.1139**	**B_5 0.0864**	**B_6 0.1156**	**B_{13} 0.1284**	**C_7 0.1011**	**C_8 0.1201**	**C_9 0.1208**	**C_{14} 0.0911**	**CC Values**	**Ranking Position**
P_1	5.00	3.00	3.00	2.00	4.00	3.00	5.00	1.00	3.00	0.5462	14
P_2	5.00	3.00	2.00	4.00	5.00	2.00	5.00	1.00	4.00	0.5948	7
P_3	4.00	4.00	3.00	4.00	4.00	3.00	3.00	4.00	4.00	0.4790	15
P_4	5.00	4.00	2.00	2.00	4.00	3.00	2.00	5.00	3.00	0.4124	17
P_5	3.00	5.00	2.00	3.00	3.00	5.00	4.00	3.00	1.00	0.4544	16
P_6	4.00	3.00	0.00	4.00	3.00	5.00	3.00	4.00	2.00	0.3947	18
P_7	5.00	3.00	2.00	3.00	4.00	2.00	4.00	0.00	5.00	0.6052	5
P_8	4.00	2.00	3.00	5.00	4.00	3.00	2.00	1.00	5.00	0.6301	2
P_9	3.00	3.00	3.00	5.00	4.00	2.00	4.00	3.00	2.00	0.5635	12
P_{10}	3.00	4.00	2.00	5.00	2.00	3.00	3.00	2.00	1.00	0.5887	9
P_{11}	3.00	3.00	5.00	0.00	1.00	1.00	2.00	0.00	2.00	0.5951	6
P_{12}	4.00	2.00	5.00	1.00	2.00	3.00	1.00	1.00	2.00	0.5892	8
P_{13}	5.00	5.00	1.00	2.00	4.00	2.00	3.00	2.00	3.00	0.5548	13
P_{14}	4.00	5.00	2.00	1.00	3.00	2.00	3.00	1.00	2.00	0.5834	10
P_{15}	3.00	4.00	5.00	3.00	5.00	2.00	4.00	2.00	3.00	0.6151	4
P_{16}	4.00	4.00	4.00	2.00	5.00	1.00	3.00	3.00	3.00	0.5713	11
P_{17}	5.00	4.00	2.00	4.00	5.00	1.00	2.00	0.00	3.00	0.7620	1
P_{18}	5.00	3.00	2.00	2.00	4.00	2.00	2.00	1.00	3.00	0.6261	3

Specifically, numeric evaluations of input for each sensor type across criteria are reported in Table 5. The 5-point scale allowed the experts to assign numerical values to represent the performance of each sensor type when pursuing benefits and resolving challenges. For the benefits criteria, higher evaluations on the 5-point scale indicate greater benefits associated with a particular sensor type. Conversely, for the challenges criteria, higher evaluations are associated to more challenging conditions. From the perspective of TOPSIS, our goal is to maximize benefits and minimize challenges. In other words, we aim to identify sensor types that offer the highest benefits while simultaneously encountering the least challenging conditions. By employing TOPSIS, we can systematically compare and rank sensor types based on their overall performance across both benefits and challenges criteria. This allows us to identify the most suitable sensor types that represent the most effective trade-off between maximizing benefits and minimizing challenges.

Values of Closeness Coefficient derived from the TOPSIS application are reported in Table 5, along with ranking positions for each sensor type. It is important to note that this first TOPSIS iteration was conducted using criteria weights obtained by normalizing values of prominence obtained from the previous Fuzzy DEMATEL procedure. With that specific weight composition, sensors types to be installed with priority would be, in order, motion sensors (P_{17}), wireless sensors (P_8), and ambient light sensors (P_{18}). By prioritizing the installation of these sensor types based on their benefits and challenges, aviation facilities can enhance operational efficiency, ensure regulatory compliance, and minimize environmental impact, ultimately contributing to the sustainable and resilient development of the aviation industry within the circular economy framework. Motion sensors play indeed a crucial role in monitoring human movement and detecting any unauthorized access to restricted areas, ensuring security and safety measures are upheld within aviation facilities. Additionally, by eliminating the need for wired connections, wireless sensors offer greater flexibility and ease of deployment, enabling seamless integration into existing infrastructure and providing real-time data transmission to monitoring systems. Lastly, ambient light sensors contribute to energy conservation efforts by regulating artificial lighting based on natural light availability, reducing energy consumption and operational costs while aligning with circular economy principles of resource efficiency and waste reduction.

Figure 4 shows a 3D view of the ranking result, displaying the closeness coefficient values for each sensor type along with the intensity of the contribution given to the ranking by the evaluations under the most prominent benefits and challenges as per Fuzzy DEMATEL results, that we remind to be B_{13} (smart production network), B_3 (improved productivity and efficiency), C_9 (data management and processing related challenges), and C_8 (precision and accuracy related challenges). In this representation, sensors occupying the first three positions of the ranking are highlighted in a different color. The heights of the bars correspond to CC values, while the widths of the bars denote the evaluations assigned by the expert team under the most prominent criteria.

As a final part of our analysis, we are going to proceed by leading a comprehensive sensitivity analysis by varying criteria weights to evaluate the robustness of the solution.

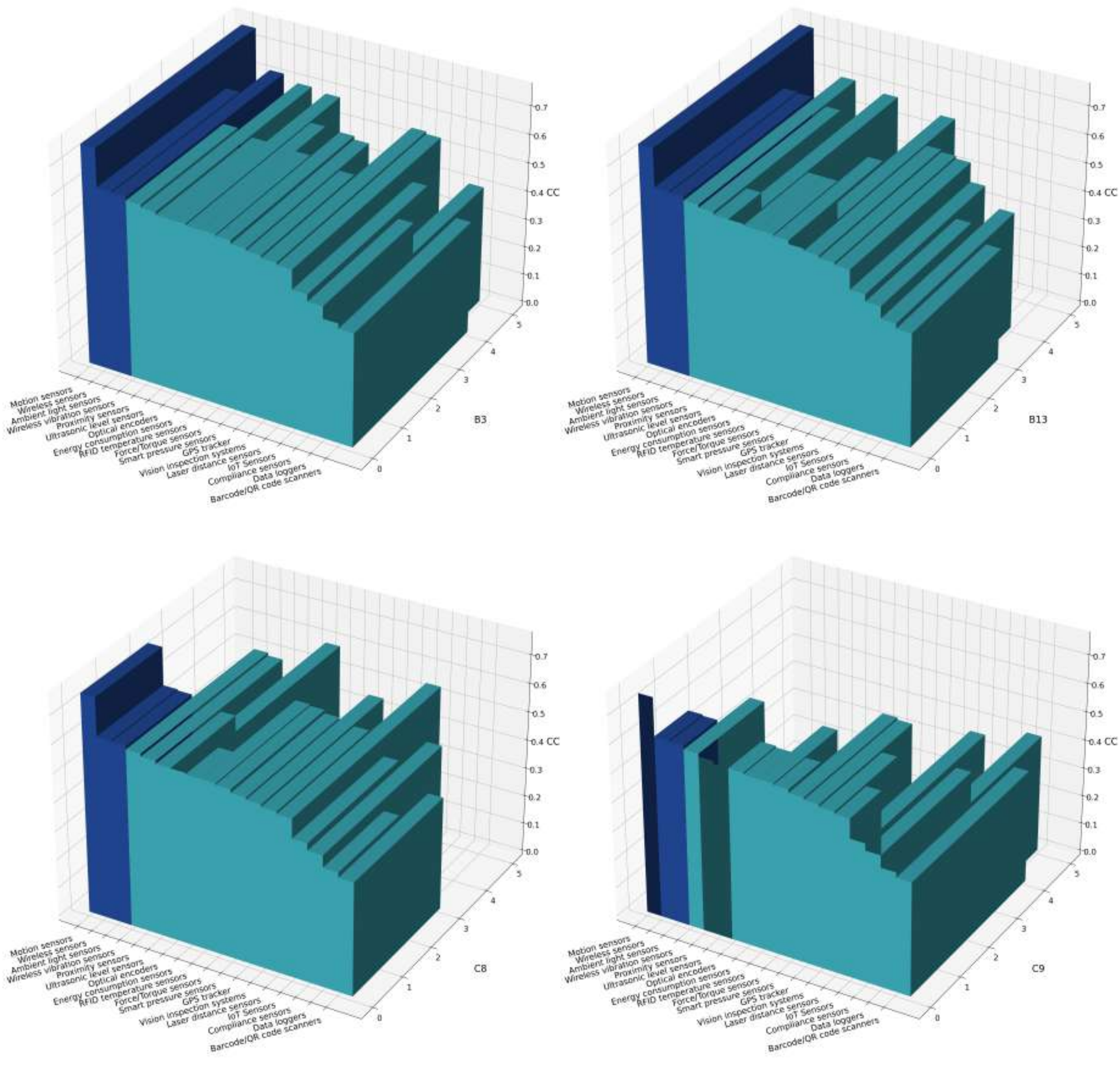

Fig. 4. Visualization of TOPSIS results in terms of CC and intensity of evaluation under the most prominent benefits and challenges

4.4 Discussion of results and managerial insights

To evaluate the robustness of the previously obtained ranking, we are going to conduct a sensitivity analysis by varying the weights that were assigned to each criterion via Fuzzy DEMATEL. Particularly, we will increase and decrease each weight attributed to the group of challenge criteria while distributing the difference due to the increase and decrease to the criteria belonging to the benefit group. In such a way, considering a variation range set at 10%, 20% and 30%, we will have in total six different scenarios of weights apart from the baseline scenario (BS) carried out in the previous subsection. Weight scenarios are reported in Table 6, each of them corresponding to a different TOPSIS iteration (related CC values are reported in Table 7).

- S_1: the first scenario refers to an increase of 30% for each criterion belonging to the challenge group (C_7 to C_{14}), and corresponding decrease for each criterion belonging to the benefit group (B_3 to B_{13}). By

Table 6. Sensitivity analysis scenarios

ID	B_3	B_4	B_5	B_6	B_{13}	C_7	C_8	C_9	C_{14}
BS	0.1226	0.1138	0.0865	0.1156	0.1285	0.1011	0.1202	0.1208	0.0910
S_1	0.0966	0.0878	0.0605	0.0896	0.1025	0.1314	0.1563	0.1570	0.1183
S_2	0.1486	0.1398	0.1125	0.1416	0.1545	0.0708	0.0841	0.0846	0.0637
S_3	0.1053	0.0965	0.0692	0.0983	0.1112	0.1213	0.1442	0.1450	0.1092
S_4	0.1399	0.1311	0.1038	0.1329	0.1458	0.0809	0.0962	0.0966	0.0728
S_5	0.1139	0.1051	0.0778	0.1069	0.1198	0.1112	0.1322	0.1329	0.1001
S_6	0.1312	0.1224	0.0951	0.1242	0.1371	0.0910	0.1082	0.1087	0.0819

Table 7. Values of Closeness Coefficient CC obtained by iterating TOPSIS in diverse weight scenarios

ID	BS	S_1	S_2	S_3	S_4	S_5	S_6
P_1	0.5462	0.5484	0.5431	0.5478	0.5441	0.5470	0.5452
P_2	0.5948	0.5775	0.6158	0.5825	0.6089	0.5883	0.6017
P_3	0.4790	0.4064	0.5691	0.4278	0.5383	0.4521	0.5080
P_4	0.4125	0.3796	0.4567	0.3889	0.4415	0.3999	0.4265
P_5	0.4542	0.4272	0.4895	0.4348	0.4775	0.4439	0.4655
P_6	0.3947	0.3629	0.4285	0.3725	0.4178	0.3832	0.4064
P_7	0.6052	0.6180	0.5843	0.6147	0.5920	0.6105	0.5990
P_8	0.6303	0.6215	0.6405	0.6241	0.6372	0.6270	0.6337
P_9	0.5635	0.5215	0.6136	0.5338	0.5970	0.5479	0.5801
P_{10}	0.5886	0.5955	0.5804	0.5935	0.5831	0.5912	0.5859
P_{11}	0.5951	0.6890	0.5047	0.6584	0.5332	0.6269	0.5636
P_{12}	0.5893	0.6546	0.5246	0.6340	0.5447	0.6121	0.5666
P_{13}	0.5547	0.5780	0.5257	0.5714	0.5353	0.5636	0.5452
P_{14}	0.5833	0.6473	0.5105	0.6280	0.5344	0.6065	0.5590
P_{15}	0.6151	0.5790	0.6601	0.5894	0.6451	0.6015	0.6298
P_{16}	0.5714	0.5494	0.6000	0.5556	0.5903	0.5629	0.5806
P_{17}	0.7620	0.7953	0.7203	0.7858	0.7342	0.7746	0.7483
P_{18}	0.6261	0.6815	0.5612	0.6651	0.5827	0.6465	0.6046

iterating TOPSIS, it appears that P_{17} (motion sensors) is the alternative remaining on top of the ranking, as automation makes the processes more efficient thanks to the accuracy of the data collected and their processing. However, we can observe in Table 7 as alternative P_{11} (ultrasonic level sensors) occupies the second place in the ranking, differing from BS scenario, where solution P_8 (wireless sensors) represented the second most suitable choice in prioritizing sensors installation. In any case, this is aligned with the practical context as increasing weights for challenges leads to major concern in precision and accuracy, as well as data management and processing. In such a direction, prioritizing ultrasonic level sensors can lead to significant improvement in the mentioned aspects.

- S_2: the second scenario refers to a decrease of 30% for each criterion belonging to the challenge group (C_7 to C_{14}), and corresponding increase for each criterion belonging to the benefit group (B_3 to B_{13}). By iterating TOPSIS, it appears that P_{17} (motion sensors) is still the alternative remaining on top of the ranking. As we can observe in Table 7, in this case alternative P_{15} (wireless vibration sensors) occupies the second place in the ranking, differing from both BS and S_1 scenarios. This outcome is justified by the evidence that these types of sensors significantly contribute to the real-time monitoring

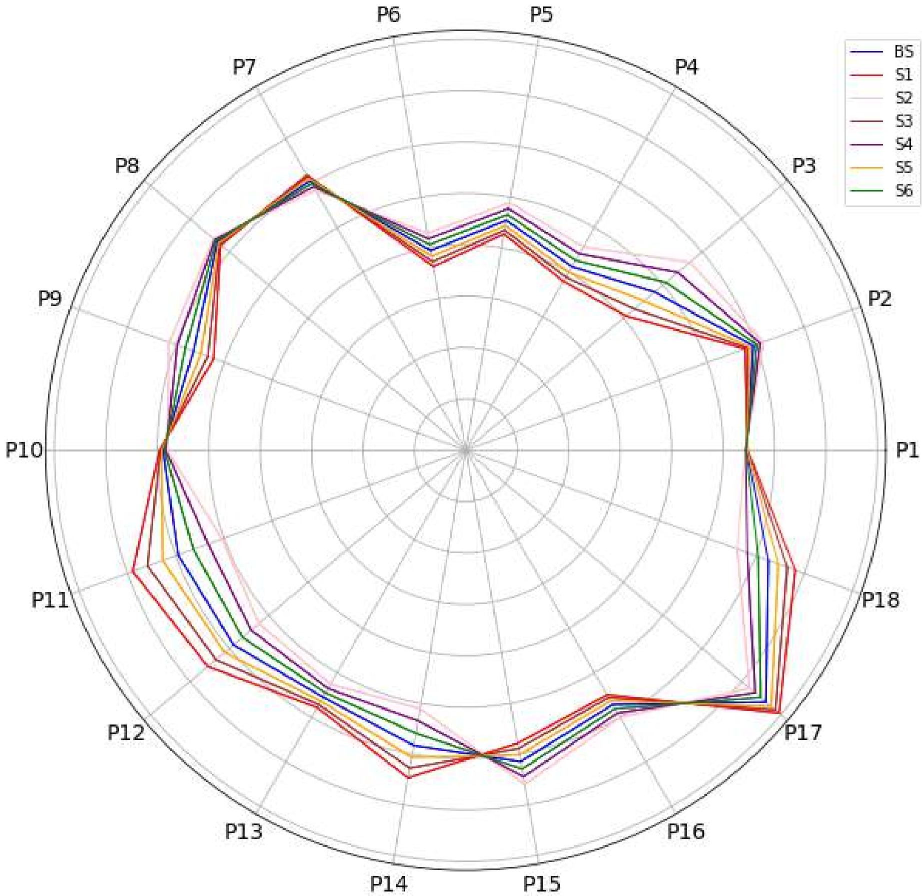

Fig. 5. Sensitivity analysis results

of machines and production plants, and can effectively detect anomalies in machine vibrations, signaling potential imminent failures and enabling predictive maintenance interventions, thus improving the level of productivity and efficiency in the aircraft sector.

- S_3: the third scenario refers to an increase of 20% for each criterion belonging to the challenge group (C_7 to C_{14}), and corresponding decrease for each criterion belonging to the benefit group (B_3 to B_{13}). By iterating TOPSIS, P_{17} (motion sensors) is the alternative remaining on top of the ranking and, as we can observe in Table 7, alternative P_{18} (ambient light sensors) represents the second most suitable option in prioritizing sensors installation. This results is motivated by the fact that a 20% percent increase of challenge weights causes a small variation on the B_3 criteria, which appears to be closely related to promoting comfortable and productive work spaces while reducing energy consumption and costs.
- S_4: the fourth scenario refers to a decrease of 20% for each criterion belonging to the challenge group (C_7 to C_{14}), and corresponding increase for each criterion belonging to the benefit group (B_3 to B_{13}). By iterating TOPSIS, P_{17} (motion sensors) is still the preferable alternative, while P_{15} (wireless vibration sensors) occupies the second place in the ranking. This is again consistent with the practical context of reference, as decreasing weights associated to challenge criteria leads to an increase in benefits and

in particular in criterion B_{13}, associated with the highest weight in the present scenario, which can be strongly emphasized by improving monitoring for machinery and equipment.

- S_5: the fifth scenario refers to an increase of 10% for each criterion belonging to the challenge group (C_7 to C_{14}), and corresponding decrease for each criterion belonging to the benefit group (B_3 to B_{13}). Alternative P_{17} (motion sensors) remains as a preferable solution, while alternative P_{18} (ambient light sensors) represents the second most suitable option in prioritizing sensors installation. Also in this case, we can highlight as P_{18} is closely correlated with benefit the B_3, being the last one associated with one of the highest weights compared to the other criteria.

- S_6: the sixth scenario refers to a decrease of 10% for each criterion belonging to the challenge group (C_7 to C_{14}), and corresponding increase for each criterion belonging to the benefit group (B_3 to B_{13}). By iterating TOPSIS, P_{17} (motion sensors) is still the alternative remaining on top of the ranking, while alternative P_8 (wireless sensors) occupies the second place in the ranking. This solution reflects the results obtained from the baseline scenario, as P_8 appears to be correlated with criteria B_3, B_6, B_{13} and C_{14}, which are associated to highest weight values compared to other criteria.

The sensitivity analysis results consistently point to P_{17} as the most favorable option across all six scenarios examined. This underscores the reliability and effectiveness of the solution associated with P_{17} under different operational conditions scrutinized in the analysis. Additionally, for visual clarity, Figure 5 presents a comparative view of the CC solutions across the scenarios. Notably, the sparse intersections of the curves highlight the robustness of the model, indicating that parameter variations have minimal impact on the system's performance.

5 Conclusions

This paper thoroughly examines the benefits and challenges of implementing Digital Twins in aviation, with a specific focus on sustainability improvements. We propose a hybrid methodological approach tailored to aviation's transition to circular business models, particularly in commercial aircraft fleet management. Expert input and the Fuzzy DEMATEL method are first used to weigh the most significant benefits and challenges emerged from literature, by considering their interdependencies and importance in Digital Twin implementation. Secondly, parameters associated with sensor installation are ranked using the TOPSIS methodology, prioritizing those that align with circular economy principles to maximize benefits and minimize barriers. A final sensitivity analysis led across diverse weight scenarios consistently shows the usefulness in prioritizing the installation of motion sensors, essential components for monitoring human movement and detecting unauthorized access to restricted areas within aviation facilities. Their role is critical in upholding security and safety measures, ensuring the protection of personnel and assets. By continuous surveillance activity, these sensors contribute to maintaining the integrity of security protocols and swiftly alert authorities to any potential breaches, thereby mitigating risks and maintaining a secure environment within aviation premises.

These types of sensor contribute to operational efficiency by tracking KPIs such as fuel consumption and flight duration, aiding in route optimization and overall effectiveness. They also optimize maintenance by identifying wear patterns in aircraft components, enabling proactive scheduling to minimize downtime and costs. It is also worth to mention as motion sensor data enhances safety by detecting anomalies in flight patterns, allowing for timely intervention to prevent accidents. Additionally, it quantifies environmental impact, aiding in carbon emission reduction and sustainability measures. By tracking resource consumption, airlines optimize utilization, identify waste reduction areas, and enhance operational efficiency. They also enable real-time flight path optimization for cost and environmental impact reduction. Lastly, motion sensor data ensures compliance with aviation regulations, maintains a safe operating environment, and enhances passenger comfort and satisfaction, fostering loyalty and positive brand perception. In conclusion, the proposed framework offers actionable insights, enhancing sustainability and operational efficiency in aviation manufacturing. Findings of this research can help companies select KPIs related to resource management, safety, and environmental impact, optimizing DT integration benefits while minimizing related challenges.

Future research could explore several areas to further advance the integration of motion sensors in aviation. One avenue is investigating the application of predictive analytics models to anticipate maintenance needs and operational disruptions, leveraging historical data and machine learning algorithms. Another promising direction is examining the role of autonomous systems, like drones equipped with sensors, for surveillance and inspection tasks, particularly in remote or hazardous areas. Lastly, exploring dynamic risk assessment models and human behavior analysis using motion sensor data can provide valuable insights for enhancing security protocols and operational effectiveness within aviation facilities.

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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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We attest that all authors contributed significantly to the creation of this manuscript. We confirm that the manuscript has been read and approved by all named authors.

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