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Evaluating the impact of Industry 4.0 on circular supply chain key performance indicators: A comparative multi-criteria decision-making analysis

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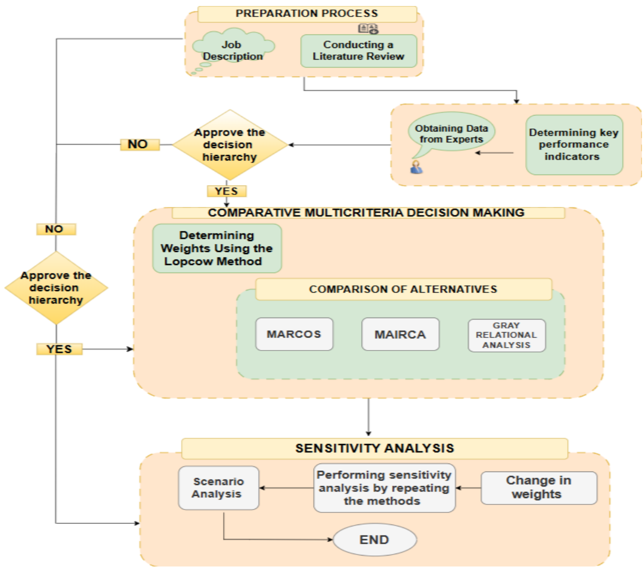
ABSTRACT

Context—With the emergence of Industry 4.0 (I4.0), supply chains have rapidly begun to digitize with technologies such as the Internet of Things (IoT), big data, artificial intelligence, blockchain, and digital twins. However, the need for sustainability, efficient use of resources, sustainable development goals (SDGs), and waste reduction strategies has created a demand to transition from linear to circular supply chains (CSC).

Objective—Research on the key performance indicators (KPIs) required to measure the success of these interrelated innovations is limited. This study aims to prioritize I4.0 technologies by weighting the performance indicators used in CSCs using an integrated decision-support approach.

Method—In expert evaluations, the Logarithmic Percentage Change-Focused Objective Weighting (LOPCOW) method was used to weight the criteria related to temporal, operational, social, environmental, and economic aspects. Technologies introduced with I4.0 and increasingly used in supply chains in recent years have been defined as alternatives. To rank these technologies, the Measurement of Alternatives Ranking and Compromise Solution (MARCOS), Grey Relational Analysis (GRA), and Multi-Attribute Ideal-Actual Comparative Analysis (MAIRCA) methods were used. The selection of decision-making methods, such as LOPCOW for objective weighting and MARCOS, GRA, and MAIRCA for ranking, provides a robust triangular verification to evaluate the results. It minimizes the inherent subjectivity of expert assessments while enabling a multidimensional evaluation of circular economy performance metrics. Also, to assess the reliability and validity of the results, five different scenario analyses were applied to all alternative evaluation methods.



Results—The results revealed that automation and smart production systems, cloud computing, robotics, and artificial intelligence technologies will enhance circular supply chain performance. The multi-criteria analysis results indicate that 'Automation and Smart Production Systems' consistently placed first across nearly all evaluation techniques. The sensitivity analysis results for each alternative evaluation method also demonstrated that the overall evaluation was consistent and valid.

Conclusion—The study underscores the strategic significance of 'Automation and Smart Production Systems' for operational efficiency and sustainability in circular supply chains, providing a validated framework for prioritizing digital investments in the circular economy. Finally, the proposed integrated decision-making framework provides a roadmap for practitioners and policymakers on which digital investments should be prioritized in line with circular economy principles. This approach ensures that industrial revolutions in supply chains are not only technologically advanced but also environmentally and economically viable.

Key Words—Circular supply chain, Industry 4.0, Key performance indicator, Multi-criteria decision-making.

I. INTRODUCTION

Today's manufacturing sector is undergoing a significant transformation driven by the rise of digital technologies and the growing importance of sustainability. At the center of this transformation lies I4.0, a revolutionary approach to manufacturing. Introduced in Germany in 2013, this approach is considered the beginning of digitalization processes in supply chains [1]. In order to improve the performance of manufacturing businesses or supply chains, I4.0 refers to a collection of technologies, organizational concepts, and management principles that are motivated by mass customization requirements, production cost optimization, factory digitization, and connectivity [2]. This new perspective, which enables the integration of new information technology-based technologies with physical production systems, has accelerated the integration of technologies such as Artificial Intelligence (AI), Internet of Things (IoT), sensors, blockchain, 3D printing, automation, and additive manufacturing into processes within the sector. Through these developments, companies can more easily respond to individual customer demands, enabling the production of customized products and allowing quality management processes to be carried out more effectively. Therefore, I4.0 is not only a technological innovation but also a comprehensive approach that aims to support sustainability goals such as flexibility, efficiency, and environmental compatibility in production [3]. The term "Industry 4.0" refers to a production process that is integrated, optimized, service-oriented, and interoperable and is associated with big data, algorithms, and advanced technology [4]. In I4.0, intelligent production is crucial. To enable them to sense, act, and behave in a smart environment, ordinary resources are transformed into intelligent objects [5]. In the literature, the phrase "smart" refers to applications of I4.0 that exhibit intelligence and knowledge [4]. I4.0's primary uses are in smart manufacturing and factories, smart products, and smart cities [6]. The basic technologies used in these areas are IoT, cloud services, big data and analytics [7]. I4.0 and the circular economy are supported by an increasingly "service-oriented" digital technology framework made possible by the smart supply chain. On the one hand, the creation and delivery of increasingly sophisticated and "service-oriented" solutions are supported by I4.0, which places the client at the center. On the other hand, I4.0 pushes more ecologically friendly procedures and emphasizes sustainability due to the substantial resource and emission savings that may be achieved [8]. Multiple interdependencies between different performance criteria for circularity, economic, environmental, and social performance are what define circular supply chain management. To identify effective activities, engage stakeholders, and minimize unintended repercussions of actions, a performance assessment system that takes these dependencies into account is currently lacking [9].

The Circular Economy is a regenerative system that slows, closes, and narrows material and energy cycles to reduce resource input, waste, emissions, and energy leakage. Long-lasting design, upkeep, repair, reuse, remanufacturing, refurbishing, and recycling may accomplish all of this [10]. Due to resource constraints, circular economies have become economically balanced systems that prioritize social, economic, and environmental challenges while improving the standard of living in congested and underdeveloped communities [11]. Thus, in order for companies to improve both their environmental and operational performance today, it is becoming increasingly important for them to evaluate I4.0 technologies and the circular supply concept in an integrated manner. The circular economy is thought to be the most appropriate and comprehensive approach to supply chain transformation in the age of I4.0. This enables the development of a high-tech industrial environment while integrating sustainable resource management [12]. I4.0 and the circular economy are approaches that are candidates for being on two sides of the same coin [13]. By lowering resource consumption and emissions from industrial operations, I4.0 techniques can be applied to maximize sustainable solutions and strengthen a circular economy [14]. The combination of these two approaches has the potential to create transformation in production systems as well as achieve sustainability goals. It can offer solutions to challenges faced by businesses, such as achieving high efficiency and reducing environmental impacts. In this context, circular supply chain performance indicators form a critical basis for assessing the applicability of I4.0 technologies and generating new solution alternatives. Metrics or tools used to measure and evaluate the circularity performance of products, businesses, sectors, or economies are referred to as circularity indicators [15]. This study aims to classify performance indicators that seek to enhance economic and environmental sustainability by evaluating both concepts together and to select alternative technologies that meet these indicators.

This study, prepared in this context, analyzes the effects of I4.0 technologies on the key performance indicators (KPI) of the circular supply chain using Multi-Criteria Decision Making (MCDM) methods. The study aims to determine which technologies provide more effective results in achieving environmental sustainability and efficiency goals. KPIs that can be used to improve supply chain processes were defined, and expert opinions were calculated using the LOPCOW method to determine the importance levels of these indicators. New MCDM methods introduced in recent years, such as MARCOS, GRA, and MAIRCA, were used to evaluate the performance of alternative technologies. The use of multiple method combinations increased the reliability of the analyses, enabling a more comprehensive and balanced evaluation. Scenario analysis was also performed to assess the validity and reliability of the results. This research aims to contribute to academic literature and establish a link between KPIs and technologies related to sustainability and digital transformation for industry professionals. In this context, the developed analytical framework reveals the effects of the integration of I4.0 technologies into the circular supply chain on performance using a multidimensional approach. The most significant methodological contribution of this study is the development of a new, integrated multi-stage MCDM framework that combines a multi-algorithm ranking approach with weighting. Unlike traditional studies in literature, which generally rely on single weighting and ranking logic, this framework offers a triangular ranking verification mechanism by simultaneously utilizing the MARCOS, GRA, and MAIRCA algorithms. This integration enables a multidimensional evaluation by simultaneously considering proximity to ideal solutions, relational patterns, and empirical gap analysis. Furthermore, by employing the LOPCOW method, the methodology systematically eliminates the subjectivity inherent in variance-based expert evaluations, thereby ensuring the mathematical integrity and robustness of the KPI prioritization process in circular supply chains. This study's sections are arranged as follows. Section II provides a comprehensive explanation of the proposed methodology, while Section III presents the results of the case study, discussion, and sensitivity analysis. Section IV includes the conclusions and recommendations for future research.

A. Literature Review

A comprehensive literature review was conducted to investigate the relationship between I4.0 technologies and CSC indicators and to highlight the gap in the literature. The review was conducted using keywords such as “I4.0,” “circular supply chain,” “key performance indicator,” and “multi-criteria.” The contributions and methodologies of the studies reviewed for the literature review are presented in Table 1. This literature review highlights the originality of the proposed approach.

Although the existing literature comprehensively addresses the intersection of I4.0 and the management of circular economy

Table 1. Summary of literature review.

Ref.	Purpose	Method
[27]	The main objective of the article is to prioritize key performance indicators to measure the effectiveness of the circular economy transition in healthcare supply chains.	Analytic Hierarchy Process (AHP)
[75]	This study aims to increase the efficiency of logistics services in the air transport sector through I4.0 technologies.	Best-Worst Method (BWM), COmprehensive BaRgain Analysis (COBRA)
[76]	This study aims to develop a performance measurement system that considers the interdependencies between circularity, economic, environmental, and social performance targets in circular supply chain management.	Multi-case analysis method
[77]	This study aims to integrate blockchain technology and a MCDM approach to implement a dynamic circular economy in the construction sector.	AHP
[78]	This study was conducted to rank the impact of I4.0 technologies on the company's production strategy outputs.	AHP/TOPSIS
[28]	The objective of this study is to improve the performance of hospitals' circular supply chains, particularly by evaluating key performance indicators in intensive care units.	Intuitive Fuzzy Delphi, Fuzzy Cognitive Mapping, (FDEMATEL)
[79]	Evaluating supply chain resilience and its impact on key performance indicators from the perspective of I4.0 and sustainability.	Fuzzy Analytic Hierarchy Process (FAHP)
[80]	The purpose of this article is to present an approach based on I4.0 and the Triple Bottom Line principles for the development of a sustainable supply chain in the renewable energy sector.	Fuzzy Logic, AHP
[81]	This article aims to evaluate the relationship between I4.0 and the circular economy that could contribute to supply chain management performance.	Modeling (ISM),v(cross-effect matrix product applied to classification) MICMAC
[82]	The primary objective of this article is to examine the critical success factors for implementing blockchain-based CSCs.	Fuzzy cognitive mapping-Fuzzy best-worst method (FCM-FBWM)
[16]	This study aims to develop a framework that defines the main stages of the Blockchain-supported Circular Supply Chain and evaluates the critical success factors for Blockchain implementation in the Circular Supply Chain.	AHP, DEMATEL
[17]	This study examines the uncertainties companies face during their transition to a circular economy and investigates the impact of circular solutions on value chain processes.	Literature Review
[18]	The purpose of this article is to present a new fuzzy performance measurement model for I4.0 in small and medium-sized manufacturing companies.	AHP, Weighted scoring methodology (WSM)
[19]	The purpose of this article is to create a model that will help pharmaceutical industries adopt supply chain management within their own organizations.	FUCOM (Full Consistency Method), F-FUCOM (Fuzzy FUCOM)
[20]	This study aims to examine the risks encountered during the transition from a linear economy to a circular economy (CE) and to offer I4.0-based solutions.	Fuzzy AHP and TODIM
[21]	This study presents a systematic literature review examining the use of MCDM methods in sustainable supply chain management.	Literature Review
[22]	The main objective of this study is to evaluate the barriers related to CSCs during the I4.0 transition period.	COmpined COmpromise SOlution (COCOSO), CRiteria Importance Through Intercriteria Correlation (CRITIC)
[23]	This study aims to analyze and rank key performance indicators (KPIs) for supply chain management in small and medium-sized enterprises (SMEs)	Balanced Scorecard (BSC) and SCOR Model Usage, Principal Component Analysis (PCA), TOPSIS
[24]	This article aims to review the latest articles in the fields of I4.0, sustainable production, and circular economy, and to develop a research framework that outlines the fundamental approaches.	Literature Review
[25]	The purpose of this study is to analyze the financial performance of automotive companies operating in Türkiye in the I4.0 environment.	GRA
[26]	This article was conducted with the aim of prioritizing the fundamental challenges of I4.0 for effective I4.0 concepts for supply chain sustainability.	AHP, Exploratory Factor Analysis (EFA)

processes, there remains a significant research gap regarding the integrated prioritization of digital technologies alongside multidimensional circular economy performance indicators. Indeed, as stated in Table 1, the current literature lacks studies specifically evaluating I4.0 technologies tailored to enhance CSC performance indicators.

Most current studies focus on a single technological aspect, such as blockchain or IoT, or use traditional MCDM methods that may not fully reflect the inherent uncertainties and interdependencies of circularity metrics [27], [28]. On the other hand, there are studies that examine KPIs specific to circular supply chains without an I4.0 framework [29], [30]. Additionally, there is a lack of methodological triangulation that combines weighting mechanisms with multi-criteria ranking algorithms to validate the strategic importance of I4.0 investments based on operational, environmental, and economic KPIs. The current study addresses this gap by focusing on the selection of I4.0 technologies necessary to improve circular supply chain indicators through a multi-layered decision-making framework that mathematically validates the findings through comprehensive sensitivity and scenario analyses.

II. PROPOSED METHODOLOGY

The proposed methodology in this study, which examines digital transformation and sustainability indicators, is designed to address the inherent complexity and uncertainty of expert opinions. The key contribution of this integrated approach lies in its holistic structure, which balances data-driven objectivity with strategic prioritization. The LOPCOW method ensures that criterion weights are derived from the intrinsic contrast of the data (standard deviation and mean square values) rather than from biased human judgment, while the three different algorithms applied subsequently (MARCOS, GRA, and MAIRCA) have established a comparative validation approach. This approach ensures that prioritized I4.0 technologies are not selected based solely on a single mathematical perspective but also consistently outperform others across different decision-making logics. The reason for adopting different MCDM ranking methods is to overcome method-dependent limitations and demonstrate the mathematical stability of the results in the decision-making process. This comparative analysis is a significant step in new MCDM models to demonstrate the consistency of the proposed approach against established algorithms in the literature. It can be presumed that using the various MCDM techniques confirms the reliability of the results [31]. This approach establishes a methodologically sound framework and avoids relying solely on a single mathematical perspective when prioritizing I4.0 technologies.

In the first phase of the study, evaluation criteria and alternative technologies were determined through a literature review and expert input. The LOPCOW method has been used to determine the criterion weights objectively. MARCOS, MAIRCA, and GRA methods have been applied to rank the alternatives according to their performance. With this integrated MCDM approach, the contribution levels of I4.0 technologies to circular supply chain performance have been analyzed multidimensionally.

A. Definition of alternatives and criteria

The criteria and alternatives were determined through in-depth research of the literature and interviews with experts. A total of 20 criteria were identified, comprising five criteria groups. Ten I4.0 technologies were defined as alternatives. Details regarding the criteria are provided in Table 2.

Table 2. Criteria definitions.

Criteria group names	Criteria	Description	Reference(s)
Time KPIs	Delivery Time (K1)	The time between when a customer places an order and when it is delivered to the customer	[23], [27], [32]
	Reorder Time (K2)	The time it takes for a facility to regain full functionality after an outage	[23]
	Order Delivery Time (K3)	Time required for the product to be manufactured and made ready for shipment	[23], [32]
	Delivery Accuracy Rate (K4)	Deliveries must be made on time and in full.	[27], [28], [32]
Operational KPIs	Risk Assessment Frequency (K5)	It is a metric that measures how often the supply chain undergoes risk assessments	[22]
	Supplier Performance Ratio (K6)	Suppliers using materials in the best possible way	[22], [33]
	Supplier Delivery Efficiency (K7)	Measures the efficiency of the supply chain	[34], [35]
	Resource Utilization Ratio (K8)	Capacity utilization is the ratio of actual output to maximum possible output.	[27], [32]
Social KPIs	Work Rate Supporting Sustainable Production (K9)	These are production processes that support sustainable production.	[33], [35]
	Employee Satisfaction (K10)	It is the level of satisfaction that employees feel towards workplace conditions, management, and their job.	[23], [28], [36]
	Renewable Energy Adoption Rate (K11)	It is a measure that shows its share in total energy consumption or production.	[27], [34], [37]
	Reuse (Repair) Rate (K12)	The rate at which products that malfunction after use are repaired and restored to working order.	[9], [27], [34], [37]
Environmental KPIs	Resource Consumption Rate (K13)	The total ecological cost of resource scarcity	[27], [37]
	Carbon Footprint Rate (K14)	The total ecological cost of the carbon footprint	[23], [27], [37]
	Green Energy Usage Rate (K15)	Promoting the use of renewable and sustainable energy sources	[27], [38]
	Material Recovery Rate (K16)	The recyclability of products	[22], [37]
Economic KPIs	Operating Cost Savings (K17)	Identify financial benefits by optimizing resource use, reducing waste, and promoting sustainability	[32], [36], [39]
	Distribution Cost (K18)	These are the logistics and transportation costs incurred during the process of delivering products to the end user.	[28], [32]
	Research and Innovation Expenses (K19)	To promote continuous research, technological advancement, and innovative solutions that support sustainability, resource efficiency, and responsible practices.	[28], [40]
	Inventory Cost (K20)	Expenses arising from the protection and storage of materials kept in warehouses and factors such as depreciation over time.	[23], [28]

The 10 alternatives selected from I4.0 technologies are shown in Fig. 1. All explanations regarding the alternatives are also given.

1. IoT

The IoT concept was first described by Kevin Ashton in 1999 [41]. By allowing physical items to "talk" to each other, exchange information, and coordinate choices, it allows physical objects to see, hear, think, and perform tasks. By utilizing its underlying technologies, such as embedded devices, communication technologies, sensor networks, Internet protocols, and applications, IoT turns these conventional things into intelligent ones [42]. Applications for the IoT are found in a wide range of fields, such as traffic control, smart energy management, smart grids, medical devices, home automation, industrial automation, senior care, and mobile healthcare services [43].

2. Cloud computing

An extension of this paradigm is cloud computing, which provides business application capabilities as advanced services accessible over a network [44]. In this system, files, applications, and various software are stored on virtual servers accessible online, rather than on personal computers or hard drives. Through this, users can access their data regardless of their geographic location, with only an internet connection required. Business owners find cloud computing interesting because it removes the need for users to schedule provisioning in advance and enables organizations to begin small and scale resources solely in response to an increase in service demand [45].

3. Big data and data analytics

Big data analytics is becoming increasingly popular in supply chain and logistics management because of its important contribution to enhancing overall business performance and complexity [46]. Data is produced by every digital procedure and social media post. Big data comes from a multitude of sources at a startling rate, volume, and diversity because of the systems, sensors, and mobile devices that broadcast this data. Accurate data transfer, analysis, and adequate processing power are necessary to extract meaningful values from big data [47].

4. Robotics and AI

Teams of robots working together and in solidarity with accomplishing certain tasks established for a specific goal are becoming more advanced, thanks to AI. Robots can do large or challenging tasks. They may also operate under hazardous or adverse circumstances. They have served as the norm for everyday tasks. Robots have appeared to be the primary source of labor, notwithstanding the costs associated with their development and upkeep. They can stop social exploitation by interacting reasonably with others [47]. AI enables computers to perceive, represent knowledge, reason, solve problems, and plan by sensing and learning inputs like those of humans. This allows computers to address complex and ill-defined problems in a deliberate, intelligent, and adaptable way [48]. The ability of a machine to perform tasks that often require human intellect, like speech recognition, natural language comprehension, and decision-making, is referred to as AI. With the help of AI, robots can sense and interact with their environment, form opinions, and complete challenging jobs [49], [50].

5. 3D printing

Defined as the process of adding materials to create objects from 3D model data (CAD models) layer by layer, 3D printing is contrary to subtractive manufacturing methodologies and is also known as rapid prototyping and rapid manufacturing [51]. In addition to providing creative production ideas to create items with more freedom in composition, structure, texture, and taste, 3D printing technology makes it possible to develop intriguing new shapes [52]. These developments encourage customized

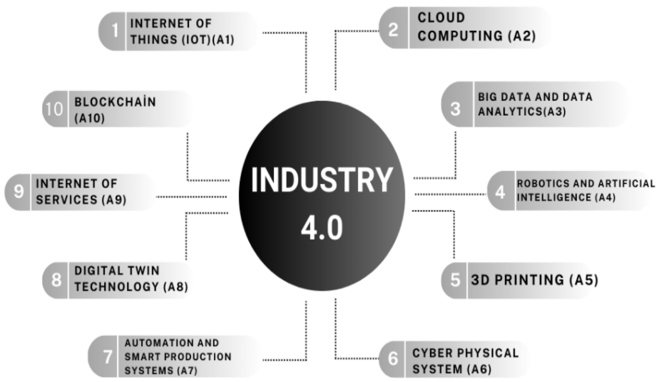


Fig. 1. Alternatives that defined as technologies.

production processes, reduce production costs, and enable the emergence of new sectors [53].

6. Cyber physical systems

The development of the IoT is based on cyber-physical systems, which make intelligent services and goods possible. Similar to how the internet has revolutionized human communication and interaction, these cutting-edge and easily accessible technologies seem set to erase the distinction between the actual and virtual worlds, indicating that they will completely change how we engage with the physical World [54]. Because of their wide range of applications, CPSs have been the subject of multiple committee meetings and studies aimed at recognizing and resolving the opportunities and problems of the future generation. Voice commands can be used to control consumer gadgets like cellphones, gaming systems, and multimedia players, and wearable technology is widely used [55]. Configurability and self-maintenance capabilities are provided to the factory by data obtained from components and machine-level information obtained from the production system via cyber systems. In addition to ensuring near-zero downtime and zero-defect production, this level of information offers plant management optimized production and inventory management plans [56].

7. Automation and Smart Production Systems

When information technologies are integrated with manufacturing processes, a new type of production known as "smart manufacturing" is created. A new paradigm in the sector has been established by the digital transformation that smart manufacturing will bring about [57]. For example, the smart production systems currently used at the Vestel Refrigerator factory include Automated Guided Vehicle (AGV) transport systems that perform transport operations without the need for an operator, laser-guided semi-finished product cutting robots, product transport and assembly robot arms, and computer-integrated data tracking systems [58]. At the supply chain level, smart factories are defined as independent establishments that purchase their raw materials from nearby vendors. Because of their proximity to suppliers and customers, those local partners and alliances have aided in reducing lead times, minimizing inventory, and simultaneously increasing supply chain customization and responsiveness [59].

8. Digital twin technology

One of the most promising enabling technologies for achieving I4.0 and smart production is the digital twin (DT). The smooth transition between the virtual and real worlds is what defines DTs [60]. A virtual dynamic model of a system, process, or service that allows advanced system analysis and thorough representation of a physical system and contains real-time data interactions is referred to as a "DT" [61]. A manufacturing DT allows for a thorough visualization of the manufacturing process from individual parts to the entire assembly and provides a chance to model and improve the production system, including its logistical aspects [62].

9. Internet of Services

A computer paradigm known as the Internet of Services (IoS) builds applications and solutions on top of services. Services are platform-independent, self-defining computational components that facilitate the quick and economic development of distributed applications. Through a self-defining interface built on open standards, services allow enterprises to programmatically expose their core competencies over the internet (or intranet) using standard (XML-based) languages and protocols [63]. For instance, social media platforms have made it simpler for users to create and share content about shared interests, while technologies like AJAX enable more flexible and dynamic data transmission between browsers and servers. Content discovery is facilitated by tagging systems. Additionally, web services provide features that both humans and machines can utilize [64].

10. Blockchain

A blockchain is a peer-to-peer digital ledger of transactions that can be shared openly or privately with all users; as such, it is referred to as decentralized and distributed technology [65]. Blockchain, which was first used in the financial sector with Bitcoin, has gradually begun to be applied in sectors such as supply chain and logistics, thanks to the traceability and security advantages it offers. This technology contributes to both speeding up processes and reducing costs by enabling the automation of transactions via smart contracts [66]. Blockchain in supply chain processes enhances product traceability, secures information flow, and builds trust among stakeholders. This prevents issues such as spoilage, delays, and counterfeiting, and allows each link in the chain to be monitored in real time.

In determining the criteria and evaluating the alternatives, the opinions of three experts with expertise in this field and relevant positions were utilized. Information about the experts is presented in Table 3. After determining the alternatives, criteria, and expert opinions, analyses were conducted. First, a LOPCOW method was used to determine the criterion weights.

B. LOPCOW method

The LOPCOW method is among the new generation of objective weighting techniques used in the MCDM process. This method imposes no restrictions on the number of criteria and can be applied to both benefit- and cost-oriented criteria without being affected by data containing negative values. Additionally, it expresses the square of the series mean as a percentage of the standard deviation, thereby eliminating differences arising from the magnitude of the data [67]. These advantages have made it a preferred choice as a criterion weighting method within the scope of this study. The related stages are listed below:

Step 1 (Obtaining the decision matrix): Creating a decision matrix that matches the problem specification is the first step. In this case, the decision matrix is organized by considering m options and n criteria that the decision maker has assessed. This matrix serves as the main data set for analysis and provides the quantitative foundation for the decision-making process. Equation (1) is used to systematically obtain this matrix.

$$\mathbf{IDM} = \begin{bmatrix} X_{11} & \cdots & X_{1j} & \cdots & X_{1n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ X_{m1} & \cdots & X_{mj} & \cdots & X_{mn} \end{bmatrix}. \tag{1}$$

Step 2 (Obtaining the normalized decision matrix): The data must be transformed into a common scale for the decision matrix to be appropriate for analysis. The direction of the evaluation of the criterion affects the normalization process. Equation (2) is used for normalization if the criteria are cost-based. On the other hand, the conversion is carried out using (3) if the criteria are benefit-oriented.

$$r_{ij} = (X_{\max} - X_{ij})/(X_{\max} - X_{\min}). \tag{2}$$

$$r_{ij} = (X_{ij} - X_{\min})/(X_{\max} - X_{\min}). \tag{3}$$

Step 3 (Creating the PV_{ij} matrix of percentage values for each criterion): At this point, (4) is used to calculate each criterion's percentage value. The criteria's mean square values are determined during the computation process by expressing them as a percentage of their standard deviations. The goal of this

Table 3. Expert information.

Expert	Experience	Education Level	Job Title
E-1	7+	PhD in Industrial Engineering	Academician
E-2	4+	BSc in Industrial Engineering	Production planning chief
E-3	3+	BSc in Industrial Engineering	Production supervisor

method is to eliminate scale differences that could result from the data set's various measurements.

$$PV_{ij} = \left|\ln\left(\left[\sqrt{\sum_{i=1}^{m} r_{ij}^2/m}\right]/\sigma\right) \times 100\right|. \tag{4}$$

Step 4 (Calculation of objective weights): At this stage, objective importance weight for each criterion is calculated using (5):

$$W_j = PV_{ij}/\sum_{i=1}^{n} PV_{ij}. \tag{5}$$

C. MARCOS method

The MARCOS method is one of the MCDM techniques and was developed in 2020. The main purpose of this method is to evaluate decision alternatives based on their proximity to ideal and anti-ideal reference points, thereby obtaining a balanced and meaningful ranking. Benefit levels are calculated based on each alternative's relationship with the reference values, enabling the identification of the alternative closest to the ideal and furthest from the anti-ideal. This structure supports decision-makers in making consistent and sustainable decisions [68]. Steps of the method are stated below:

Step 1 (Obtaining the decision matrix): A decision matrix is being created. This matrix contains the performance values of the alternatives according to the specified criteria. Each element of the matrix represents the performance level of the ith alternative in terms of the jth criterion.

Step 2 (Obtaining the extended initial matrix): As shown in (6), the ideal (AI) and anti-ideal (AAI) reference values are incorporated into the initial matrix to form an expanded decision matrix:

$$\mathbf{X^G} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \\ AI \\ AAI \end{array}\begin{bmatrix} c_1 & c_2 & \cdots & c_n \\ x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m1} & \cdots & x_{mn} \\ x_{ai1} & x_{ai2} & \cdots & x_{ain} \\ x_{aa1} & x_{aa2} & \cdots & x_{aan} \end{bmatrix}. \tag{6}$$

Different equations are used to calculate ideal (AI) and anti-ideal (AAI) reference values, depending on the nature of the criteria. For benefit-oriented criteria, (7) and (8) are considered, while for cost-based criteria, (9) and (10) are considered to determine the relevant values.

$$AAI = \begin{cases} \min_i x_{ij}, & \text{if } j \in B \\ \max_i x_{ij}, & \text{if } j \in C \end{cases} \tag{7}$$

$$AI = \begin{cases} \max_i x_{ij}, & \text{if } j \in B \\ \min_i x_{ij}, & \text{if } j \in C \end{cases} \tag{8}$$

$$AAI = \begin{cases} \max_i x_{ij}, & \text{if } j \in B \\ \min_i x_{ij}, & \text{if } j \in C \end{cases} \tag{9}$$

$$AI = \begin{cases} \min_i x_{ij}, & \text{if } j \in B \\ \max_i x_{ij}, & \text{if } j \in C \end{cases} \tag{10}$$

Step 3 (Obtaining the normalized expanded initial matrix): Different equations are used to obtain the normalized initial matrix, depending on the type of criteria. Equation (11) is used for benefit-based criteria, while (12) is used for cost-based criteria.

$$n_{ij} = x_{ij}/x_{ai},\ j \in B. \tag{11}$$

$$n_{ij} = x_{ai}/x_{ij},\ j \in C. \tag{12}$$

Step 4 (Obtaining the weighted matrix): The weighted decision matrix is created using (13). To obtain this matrix, the values in the normalized matrix N are multiplied by the weight coefficient w_j for each criterion.

$$v_{ij} = n_{ij}w_j. \tag{13}$$

Step 5 (Obtaining the utility degree of alternatives): Utility degrees are calculated for ideal and anti-ideal solutions using (14) and (15), respectively. The S_i value included in these calculations represents the sum of all criterion values for the relevant alternative in the weighted decision matrix, and this sum is determined by (16).

$$K_i^+ = S_i/S_{ai}, \tag{14}$$

$$K_i^- = S_i/S_{aai}, \tag{15}$$

$$S_i = \sum_{i=1}^{n} v_{ij}. \tag{16}$$

Step 6 (Obtaining the utility functions of alternatives): The utility function reflects the compromise solution level obtained by evaluating each alternative relative to the ideal and anti-ideal solutions. The utility values of the alternatives in this direction are calculated using (17). In this calculation, (18) shows the utility obtained relative to the ideal solution point, while (19) shows the utility level determined relative to the non-ideal solution.

$$f(K_i) = (K_i^+ + K_i^-)/\left[1 + \frac{1-f(K_i^+)}{f(K_i^+)} + \frac{1-f(K_i^-)}{f(K_i^-)}\right], \tag{17}$$

$$f(K_i^+) = K_i^-/(K_i^+ + K_i^-), \tag{18}$$

$$f(K_i^-) = K_i^+/(K_i^+ + K_i^-). \tag{19}$$

Step 7 (Ranking alternatives): Alternatives are ranked according to the final values of their utility functions. The option with the highest score is considered the most preferred alternative.

D. Grey Relational Analysis Method (GRA)

The concept of grey refers to a lack of information or the completely unknown nature of information. Over the past twenty years, grey system theory has become an effective analysis method widely used in various disciplines. This approach offers an alternative method that allows for the quantitative evaluation of uncertain data. Introduced to the literature by Deng and Wang in 1989 [69], the stages of this method are as follows [70]:

Step 1 Obtaining the decision matrix shown in (20):

$$\mathbf{X}_i = \begin{bmatrix} x_1(1) & x_1(2) & \dots & x_1(n) \\ x_2(1) & x_2(2) & \dots & x_2(n) \\ \vdots & \vdots & \ddots & \vdots \\ x_n(1) & x_n(2) & \dots & x_n(n) \end{bmatrix}. \tag{20}$$

Step 2 (Obtaining the reference series): Reference series defined by $x_1(1), x_1(2), \dots, x_1(j), \dots, x_1(n)$ is obtained, where $x_1(j)$ indicates the jth largest value within the normalized values of the criterion.

Step 3 (The normalization process is carried out in 3 stages): The standardization process for indicators with different measurement units is applied using (21) and (22), which contain the relevant calculation formulas. A special case may arise here. This situation occurs if the criterion value is desired to take an average value after the normalization process; in this case, (23) is applied.

$$x_i^*(j) = [x_i(j) - \min x_i(j)]/[\max x_i(j) - \min x_i(j)], \tag{21}$$

$$x_i^*(j) = \left[\max_j x_i(j) - x_i(j)\right]/\left[\max_j x_i(j) - \min_j x_i(j)\right], \tag{22}$$

$$x_i^*(j) = |x_i(j) - x_{0b}(j)|/\left[\max_j x_i(j) - x_{0b}(j)\right]. \tag{23}$$

As a result of these operations, the decision matrix in Eq. (20) transforms into (24).

$$\mathbf{X}_i^* = \begin{bmatrix} x_1^*(1) & x_1^*(2) & \dots & x_1^*(n) \\ x_2^*(1) & x_2^*(2) & \dots & x_2^*(n) \\ \vdots & \vdots & \ddots & \vdots \\ x_n^*(1) & x_n^*(2) & \dots & x_n^*(n) \end{bmatrix}. \tag{24}$$

Step 4 (Acquisition of the absolute value table): The differences between the coefficients are determined by considering the characteristics of the criteria. This difference represents the deviation of each criterion's ranking from the reference point. The coefficient difference, denoted by the symbol $\Delta_{0i}(j)$, is calculated using (25):

$$\Delta_{0i}(j) = |x_0^*(j) - x_i^*(j)|. \tag{25}$$

Step 5 Calculation of the coefficient matrix:

$$\gamma_{\mathrm{i}}(j) = (\Delta\min + \zeta\Delta\max)/(\Delta_{0\mathrm{i}}(j) + \zeta\Delta\max). \tag{26}$$

Equation (26) is the distinguishing coefficient and takes values in the range [0, 1]. However, it is recommended to take 0.5 in transactions [70].

Step 6 (Obtaining a relationship degree): The relationship degree is obtained using (27):

$$\Gamma_{oi} = (1/n)\sum_{j=1}^{n} \gamma_{oi}(j), \tag{27}$$

where Γ_{oi} indicates the degree of the ith element and is used when the criteria are assumed to have equal importance levels. If the criteria have different weights, (28) is used:

$$\Gamma_{oi} = \sum_{j=1}^{n} [W_i(j)\gamma_{oi}(j)]. \tag{28}$$

E. MAIRCA method

The MAIRCA method is based on examining the differences between the ideal weights determined for decision criteria and the empirical weights calculated. These differences, calculated for each criterion, constitute the total gap values of the decision alternatives. The alternative with the lowest total gap is considered the most suitable option for decision makers. This approach enables accurate assessments based on empirical data in decision support systems and stands out as a preferred method in various sectors [71].

Step 1 Definition of a decision matrix:

$$\mathbf{X} = [x_{ij}]_{m\times n} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}. \tag{29}$$

Step 2. In the second stage of the method, the preference probabilities of each alternative are determined. This calculation is performed using (30):

$$P_{Bi} = 1/m\,;\ i = 1,2,\dots,m. \tag{30}$$

The preference probabilities of the alternatives are assumed to be equal and their sum must equal 1, i.e. $\sum_{i=1}^{m} P_{Bi} = 1$.

Step 3. The theoretical evaluation matrix is obtained by multiplying the preference probabilities by the criterion weights. Equation (31) is used for this operation:

$$\mathbf{K_p} = \begin{bmatrix} k_{p11} & k_{p12} & \cdots & k_{p1n} \\ k_{p21} & k_{p22} & \cdots & k_{p2n} \\ \vdots & \vdots & \ddots & \vdots \\ k_{pm1} & k_{pm2} & \cdots & k_{pmn} \end{bmatrix} \begin{bmatrix} P_{B1}w_1 & P_{B1}w_2 & \cdots & P_{B1}w_n \\ P_{B2}w_1 & P_{B2}w_2 & \cdots & P_{B2}w_n \\ \vdots & \vdots & \ddots & \vdots \\ P_{Bm}w_1 & P_{B1}w_2 & \cdots & P_{Bm}w_n \end{bmatrix} \tag{31}$$

Step 4. At this stage, (32) is used for beneficial criteria and (33) for non-beneficial criteria to obtain the actual evaluation matrix.

$$k_{rij} = k_{pij} = (d_j - d_i^-)/(d_i^+ - d_i^-), \tag{32}$$

$$k_{rij} = k_{pij} = (d_{ij} - d_i^+)/(d_i^- - d_i^+), \tag{33}$$

where d_i^+ and d_i^- are defined as $d_i^+ = \max(d_1, \dots, d_m)$ and $d_i^- = \min(d_1, \dots, d_m)$.

Step 5. Equations (34) and (35) are used to create the total gap matrix **F**. This matrix shows the critical gaps used in evaluating decision alternatives and determines the differences between each alternative and the ideal solution.

$$\mathbf{F} = \mathbf{K}_p - \mathbf{K}_r = \begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1n} \\ f_{21} & f_{22} & \cdots & f_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ f_{m1} & f_{m2} & \cdots & f_{mn} \end{bmatrix}, \tag{34}$$

where

$$f_{ij} = \begin{cases} 0, & \text{if } k_{pij} = k_{rij} \\ k_{pij} - k_{rij}, & \text{if } k_{pij} > k_{rij} \end{cases}. \tag{35}$$

Step 6. In the final step, (36) is used to obtain an evaluation score for each alternative. These scores reveal the overall success level of the alternatives. In this method, the differences between the theoretically expected values and the actual data are taken as the basis. How close an alternative is to ideal conditions is measured by the sum of these differences. As the total difference value decreases, the alternative's compatibility with the ideal solution increases. Therefore, the alternative with the lowest total difference value is considered the most suitable option according to the logic of the method.

$$Q_i = \sum_{j=1}^{n} f_{ij}. \tag{36}$$

III. CASE STUDY

This study examines the impact of technologies within the scope of I4.0 on the circular supply chain. By pioneering the integration of LOPCOW, MARCOS, GRA, and MAIRCA, it offers a robust and comprehensive methodology for tackling complex MCDM problems. The process begins with LOPCOW, where experts compare the relative importance levels of the criteria to determine their weights. Expert opinions are evaluated by accurately representing the hierarchical structure of criteria. In the CSC context, this enhanced framework provides a robust mechanism for prioritizing I4.0-compatible criteria, enabling more accurate and reliable weighting of performance indicators. Subsequently, the MARCOS, GRA, and MAIRCA methods are used to rank alternatives based on their performance in the defined criteria.

Fig. 2 shows a detailed flowchart illustrating the logical progression and practical applicability of the proposed LOPCOW-MARCOS-GRA-MAIRCA methodology.

A. LOPCOW findings

The LOPCOW method was applied to determine the criterion weights. MS Excel was used to solve LOPCOW. Accordingly, a total of 20 criteria were determined for use in the evaluation of I4.0 technologies, and these criteria were classified into five main categories: temporal performance, operational, social, environmental, and economic. The criteria table created is shown in Table 2. The stages of the LOPCOW method are shown below.

Step 1. In the first phase of the research, the criteria in question were defined in detail and structured to serve as a reference during the analysis process. As a result of the evaluations, I4.0 technologies that support circular supply chain performance at the highest level were identified. These technologies were defined as alternatives. Three separate evaluation forms were applied to decision-makers to determine the most effective and least effective criteria in each criterion group. Participants were then asked to score the criteria they identified as the strongest and weakest against other criteria using the evaluation scale

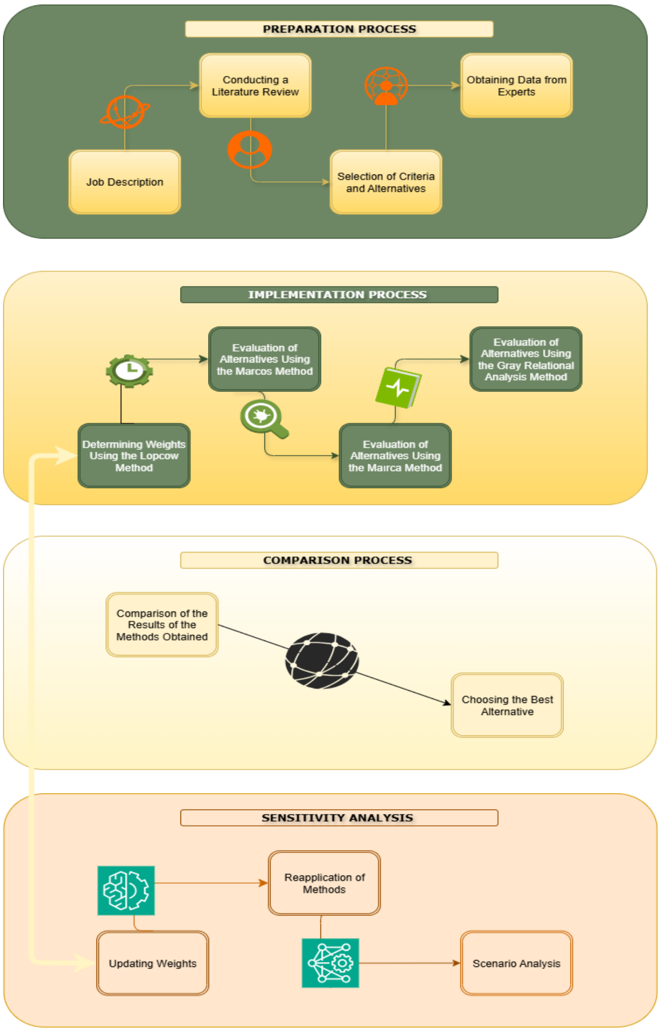


Fig. 2. The flowchart of the proposed methodology.

presented in Table 4. Based on the data obtained, it was determined whether each criterion was benefit- or cost-oriented and which criteria should be preferred for maximum or minimum values.

Step 2. At this stage, the three separate evaluation forms obtained from the experts were combined to create a single initial decision matrix. In combining the expert opinions, the geometric mean of the values obtained for each criterion was taken to obtain the final initial decision matrix. Equation (1) was used when creating the decision matrix. Table 5 shows an evaluation matrix for a sample expert. The geometric mean of these numbers from each evaluator was taken to create the integrated initial decision matrix in Table 6.

Step 3. Normalization is performed based on the criterion direction. If the criteria are cost-based, normalization is performed using (2). Conversely, if the criteria are benefit-oriented, the transformation is performed based on (3). Subsequently, the values of each criterion are squared. Next, the performance values (PV_{ij}) related to the criteria are calculated based on the standard deviation and arithmetic mean ratio. These calculations are performed based on (4) of the LOPCOW method, and the obtained PV_{ij} values are transferred to the next stage to be used in determining the criterion weights. The calculated values are shown in Table 7.

Table 4. Linguistic scale [83]

Score	1	2	3	4	5	6	7
Value	Very bad	Bad	A little bad	Middle	Good	A little good	Very good

Table 5. Initial decision matrix of E-1.

	Alternatives									
Criteria	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
K1	7	5	4	4	3	5	6	5	5	3
K2	6	4	4	5	4	4	6	3	5	2
K3	6	6	5	6	3	5	6	4	5	3
K4	5	7	4	4	3	5	7	4	7	4
K5	6	5	7	4	4	4	6	4	6	4
K6	5	6	3	6	3	6	7	4	4	5
K7	4	5	4	6	4	6	7	4	4	5
K8	4	5	4	6	4	6	7	4	4	3
K9	5	6	5	7	4	6	7	4	4	4
K10	5	2	2	6	4	6	7	4	3	2
K11	5	5	4	7	4	4	7	5	5	2
K12	5	3	2	6	2	4	6	4	3	2
K13	2	2	3	5	3	7	6	3	3	3
K14	2	2	2	7	2	6	7	4	2	1
K15	3	2	3	5	2	6	7	5	4	2
K16	6	5	5	7	3	5	6	5	2	2
K17	5	5	5	6	4	5	6	6	5	4
K18	6	3	4	5	2	6	7	2	4	2
K19	5	4	4	7	5	4	7	6	5	5
K20	6	4	3	6	3	4	6	6	4	5

Step 4. The objective importance weights of the criteria were calculated based on the PV_{ij} values obtained in the previous step. The relevant calculations were performed using the formula given in (5), and the results are presented in Table 8.

Based on the objective weights obtained, the most important criterion K17 was operating cost savings. The second most important criterion K6 is the supplier performance ratio, while the third most important criterion is K4 on-time delivery ratio. On the other hand, the least important criteria are, in order, K12 reuse/repair rate, K9 rate of working in a way that supports sustainable production, and finally K3 order fulfillment time.

B. MARCOS findings

The steps for applying the MARCOS method are as follows:

Step 1. Evaluations were obtained using the linguistic scales listed in Table 4 from experts, and a decision matrix was created. In determining the ideal (AI) and anti-ideal (AAI) reference values, different mathematical expressions were used, considering the nature of each criterion. In this context, (6) and (7) were used as the basis for determining ideal values for benefit-based criteria, while (8) was used as the basis for anti-ideal values. On the other hand, when cost-based criteria were considered, ideal values were obtained using (9), while anti-ideal values were calculated using (10). In the study, AI and AAI values were obtained by selecting appropriate equations according to the direction of the relevant criteria. Reference points reflecting ideal and anti-ideal solutions were determined accordingly, and an Extended Initial Matrix was created. The calculated values are presented in detail in Table 9.

Step 2. For benefit-based criteria, (11) was used, and for cost-based criteria, (12) was used to create the Normalized Extended decision matrix. The normalized decision matrix was multiplied by the criterion weights obtained earlier using the LOPCOW method, as shown in Table 8, to create the weighted normalized matrix as shown in (13). This process aims to refine the evaluation of alternatives by considering the relative importance of each criterion. The results are shown in Table 10.

Step 3. At this stage, the relative positions of the alternatives with respect to the ideal and anti-ideal solutions were evaluated based on the data obtained from the weighted and expanded normalized decision matrix. First, the total performance values of each alternative were calculated using (14). Subsequently, the proximity ratio of the alternatives to the ideal solution and the distance ratio to the anti-ideal solution were determined using (15). In addition, the benefit values based on the ideal solution, anti-ideal solution, and overall performance were obtained using

Table 6. Aggregated initial decision matrix.

Criterion Side	Criteria	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
Min	K1	7.319	4.932	4.642	4	2.621	5	6.952	5	5	3
Min	K2	5.241	4.642	4.309	4.642	3.634	3.302	5.646	2.289	5	2.884
Min	K3	5.646	5.313	5.313	5.313	2.621	5.313	5.646	4.309	4.642	3.302
Max	K4	4.309	6.316	4	4	1.817	5.944	7	4	7	3.302
Max	K5	5.646	5.313	7	4	4.642	4	5.646	4.642	5.313	3.634
Max	K6	5.313	5.646	3.302	5.313	1.817	5.313	7	4	4	4.642
Max	K7	4.309	5	5.518	6.649	4	5.313	6.649	3.302	4	5
Max	K8	4.309	5.313	4.579	6	4	5.646	5.809	3.302	3.915	3
Max	K9	5	6	5	7	4.932	5.646	6.257	4.309	4	4
Max	K10	5.646	2.884	3.107	6	4	6	6.316	4.932	3.634	2.289
Max	K11	4.642	4.642	4	6.257	3.302	4	6.316	5.646	5	2.621
Max	K12	5	2.621	1.587	6.316	2	4	5.313	4	3.634	1.587
Min	K13	2.289	2.621	3	5	1.817	6.316	6.649	3.915	2.289	2.289
Min	K14	2.621	2.289	2	6.649	2	5.646	6.316	4.309	2.289	1.817
Max	K15	3	1.587	3	5.313	2.289	6.649	5.944	4.642	4.642	1.587
Max	K16	6	5	5	5.944	2.621	5.646	5.313	5.313	2	2.289
Max	K17	5	4.642	5.646	4.579	4.642	5.646	5.241	4.932	4.217	3.302
Min	K18	6	3	4	5	1.817	6.649	6.649	2.289	4.642	2.621
Min	K19	4.642	4	4.309	6.649	5	4.932	6.316	6	4.309	3.915
Min	K20	5.313	4.642	1.817	6.649	3.302	4.642	5.646	6	4.309	3.915

Table 7. Calculation of PV_{ij} value.

Criterion Side	Criteria	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	PV
Min	K1	0	0.258	0.325	0.499	1	0.244	0.006	0.244	0.244	0.845	65.22
Min	K2	0.015	0.09	0.159	0.09	0.359	0.488	0	1	0.037	0.677	50.74
Min	K3	0	0.012	0.012	0.012	1	0.012	0	0.195	0.11	0.6	25.27
Max	K4	0.231	0.754	0.177	0.177	0	0.634	1	0.177	1	0.082	67.4
Max	K5	0.357	0.249	1	0.012	0.09	0.012	0.357	0.09	0.249	0	49.49
Max	K6	0.455	0.546	0.082	0.455	0	0.455	1	0.177	0.177	0.297	77.99
Max	K7	0.09	0.257	0.438	1	0.043	0.361	1	0	0.043	0.257	57.44
Max	K8	0.19	0.595	0.277	1	0.111	0.778	0.877	0.01	0.093	0	57
Max	K9	0.111	0.444	0.111	1	0.097	0.301	0.566	0.011	0	0	43.17
Max	K10	0.695	0.022	0.041	0.849	0.18	0.849	1	0.431	0.112	0	56.42
Max	K11	0.299	0.299	0.139	0.968	0.034	0.139	1	0.67	0.414	0	65.08
Max	K12	0.521	0.048	0	1	0.008	0.26	0.621	0.26	0.187	0	44.07
Min	K13	0.814	0.695	0.57	0.117	1	0.005	0	0.32	0.814	0.814	66.91
Min	K14	0.695	0.814	0.926	0	0.926	0.043	0.005	0.235	0.814	1	60.7
Max	K15	0.078	0	0.078	0.542	0.019	1	0.741	0.364	0.364	0	45.22
Max	K16	1	0.563	0.563	0.972	0.024	0.831	0.686	0.686	0	0.005	62.16
Max	K17	0.525	0.327	1	0.297	0.327	1	0.685	0.484	0.152	0	84.62
Min	K18	0.018	0.57	0.301	0.117	1	0	0	0.814	0.173	0.695	48.57
Min	K19	0.539	0.939	0.733	0	0.364	0.394	0.015	0.056	0.733	1	65.19
Min	K20	0.076	0.173	1	0	0.48	0.173	0.043	0.018	0.235	0.32	54.62

Table 8. Objective weightings of criteria.

#	W_j	Criteria
1	0.0738	K17
2	0.068	K6
3	0.0587	K4
4	0.0583	K13
5	0.0568	K1
6	0.0568	K19
7	0.0567	K11
8	0.0542	K16
9	0.0529	K14
10	0.0501	K7
11	0.0497	K8
12	0.0492	K10
13	0.0476	K20
14	0.0442	K2
15	0.0431	K5
16	0.0423	K18
17	0.0394	K15
18	0.0384	K12
19	0.0376	K9
20	0.022	K3

(16). Thus, the position of each alternative in the overall solution area was clarified, and the ranking process was initiated. Finally, the $f(K_i)$ values were obtained as in (17), and the alternatives were ranked from highest to lowest. This ranking directly guides the decision maker in determining the most suitable option. The final ranking is presented in Table 11.

As a result of the evaluation, A7 were determined to be the technology with the highest importance among I4.0 technologies. This is followed by A4, A2, and A6. Other technologies, such as A8, A9, A5, and A10, were assigned lower priorities. This ranking was based on each technology's potential to improve supply chain performance and is critical for the future I4.0 applications.

C. GRA findings

The steps of GRA analysis are defined as follows:

Step 1. First, evaluations were obtained from experts using the linguistic scale in Table 4, and a decision matrix was created [72]. This structure forms the basic data set to be used in the analysis process. Subsequently, based on the criterion values in the decision matrix, the most appropriate reference value for each criterion was determined. These values form the basis for comparing each criterion and are called the "reference series". The reference series obtained, included in the decision matrix, is shown in Table 12.

Step 2. The normalization process was performed using formula (22) for benefit-based indicators and formula (21) for cost-based criteria. The absolute values of the differences between the normalized value and the reference value for each criterion were

Table 9. Obtaining the extended initial matrix.

Criterion		Alternatives											
Side	Criteria	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	AAL	AL
Min	K1	7.319	4.932	4.642	4	2.621	5	6.952	5	5	3	7.319	2.621
Min	K2	5.241	4.642	4.309	4.642	3.634	3.302	5.646	2.289	5	2.884	5.646	2.289
Min	K3	5.646	5.313	5.313	5.313	2.621	5.313	5.646	4.309	4.642	3.302	5.646	2.621
Max	K4	4.309	6.316	4	4	1.817	5.944	7	4	7	3.302	1.817	7
Max	K5	5.646	5.313	7	4	4.642	4	5.646	4.642	5.313	3.634	3.634	7
Max	K6	5.313	5.646	3.302	5.313	1.817	5.313	7	4	4	4.642	1.817	7
Max	K7	4.309	5	5.518	6.649	4	5.313	6.649	3.302	4	5	3.302	6.649
Max	K8	4.309	5.313	4.579	6	4	5.646	5.809	3.302	3.915	3	3	6
Max	K9	5	6	5	7	4.932	5.646	6.257	4.309	4	4	4	7
Max	K10	5.646	2.884	3.107	6	4	6	6.316	4.932	3.634	2.289	2.289	6.316
Max	K11	4.642	4.642	4	6.257	3.302	4	6.316	5.646	5	2.621	2.621	6.316
Max	K12	5	2.621	1.587	6.316	2	4	5.313	4	3.634	1.587	1.587	6.316
Min	K13	2.289	2.621	3	5	1.817	6.316	6.649	3.915	2.289	2.289	6.649	1.817
Min	K14	2.621	2.289	2	6.649	2	5.646	6.316	4.309	2.289	1.817	6.649	1.817
Max	K15	3	1.587	3	5.313	2.289	6.649	5.944	4.642	4.642	1.587	1.587	6.649
Max	K16	6	5	5	5.944	2.621	5.646	5.313	5.313	2	2.289	2	6
Max	K17	5	4.642	5.646	4.579	4.642	5.646	5.241	4.932	4.217	3.302	3.302	5.646
Min	K18	6	3	4	5	1.817	6.649	6.649	2.289	4.642	2.621	6.649	1.817
Min	K19	4.642	4	4.309	6.649	5	4.932	6.316	6	4.309	3.915	6.649	3.915
Min	K20	5.313	4.642	1.817	6.649	3.302	4.642	5.646	6	4.309	3.915	6.649	1.817

Table 10. Weighted normalized decision matrix.

Criterion		Alternatives											
Side	Criteria	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	AAL	AL
Min	K1	0.02	0.03	0.032	0.037	0.057	0.03	0.021	0.03	0.03	0.05	0.02	0.057
Min	K2	0.019	0.022	0.023	0.022	0.028	0.031	0.018	0.044	0.02	0.035	0.018	0.044
Min	K3	0.01	0.011	0.011	0.011	0.022	0.011	0.01	0.013	0.012	0.017	0.01	0.022
Max	K4	0.036	0.053	0.034	0.034	0.015	0.05	0.059	0.034	0.059	0.028	0.015	0.059
Max	K5	0.035	0.033	0.043	0.025	0.029	0.025	0.035	0.029	0.033	0.022	0.022	0.043
Max	K6	0.052	0.055	0.032	0.052	0.018	0.052	0.068	0.039	0.039	0.045	0.018	0.068
Max	K7	0.032	0.038	0.042	0.05	0.03	0.04	0.05	0.025	0.03	0.038	0.025	0.05
Max	K8	0.036	0.044	0.038	0.05	0.033	0.047	0.048	0.027	0.032	0.025	0.025	0.05
Max	K9	0.027	0.032	0.027	0.038	0.027	0.03	0.034	0.023	0.022	0.022	0.022	0.038
Max	K10	0.044	0.022	0.024	0.047	0.031	0.047	0.049	0.038	0.028	0.018	0.018	0.049
Max	K11	0.042	0.042	0.036	0.056	0.03	0.036	0.057	0.051	0.045	0.024	0.024	0.057
Max	K12	0.03	0.016	0.01	0.038	0.012	0.024	0.032	0.024	0.022	0.01	0.01	0.038
Min	K13	0.046	0.04	0.035	0.021	0.058	0.017	0.016	0.027	0.046	0.046	0.016	0.058
Min	K14	0.037	0.042	0.048	0.014	0.048	0.017	0.015	0.022	0.042	0.053	0.014	0.053
Max	K15	0.018	0.009	0.018	0.031	0.014	0.039	0.035	0.028	0.028	0.009	0.009	0.039
Max	K16	0.054	0.045	0.045	0.054	0.024	0.051	0.048	0.048	0.018	0.021	0.018	0.054
Max	K17	0.065	0.061	0.074	0.06	0.061	0.074	0.068	0.064	0.055	0.043	0.043	0.074
Min	K18	0.013	0.026	0.019	0.015	0.042	0.012	0.012	0.034	0.017	0.029	0.012	0.042
Min	K19	0.048	0.056	0.052	0.033	0.044	0.045	0.035	0.037	0.052	0.057	0.033	0.057
Min	K20	0.016	0.019	0.048	0.013	0.026	0.019	0.015	0.014	0.02	0.022	0.013	0.048

Table 11. Ranking alternatives according to the MARCOS method.

Code	Alternatives	$f(K_i)$	Ranking
A1	Internet of Things (IoT)	0.615	6
A2	Cloud Computing	0.628	3
A3	Big Data and Data Analytics	0.623	5
A4	Robotics and Artificial Intelligence	0.633	2
A5	3D Printing	0.586	9
A6	Cyber-Physical Systems	0.628	4
A7	Automation and Smart Manufacturing Systems	0.656	1
A8	Digital Twin Technology	0.589	7
A9	Internet of Services (IoS)	0.587	8
A10	Blockchain	0.554	10

taken to create the difference matrix (Δ). This calculation was performed using (25). Subsequently, the grey relationship coefficients were calculated for each criterion. These coefficients were determined using (26), considering the smallest and largest values of the differences. The discriminant coefficient (ζ) is generally taken as 0.5 in literature. For this reason, it was defined as 0.5 in this study. The created Δmax, Δmin, and ζ values are 1.0, 0.0, and 0.5, respectively, and the Grey Relational Coefficient Matrix is shown in Table 13.

Step 3. Grey relationship coefficients representing the overall performance of each alternative have been obtained. These coefficients were calculated by taking the average of the relationship coefficients for all criteria and were determined using (27). When obtaining the different weights of the criteria, the weights obtained in the LOPCOW method in Table 7 were used, and (28) was used for the weighted average calculation. The obtained Equal Importance Levels and Different Importance Levels are shown in Table 14.

Step 4. The alternatives were subjected to two different rankings based on equal and different importance level values. This ranking directly guides the decision maker in determining the most suitable option. The final ranking is also shown in Table 14. According to the analysis results, similar trends were observed among the alternatives when both equal and different levels of importance were considered. In particular, A7 ranked first, achieving the highest correlation in both types of evaluation. This

Table 12. Decision matrix with added reference series.

Criterion Side	Criteria	Reference	Alternatives									
			A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
Min	K1	2.621	7.319	4.932	4.642	4	2.621	5	6.952	5	5	3
Min	K2	2.289	5.241	4.642	4.309	4.642	3.634	3.302	5.646	2.289	5	2.884
Min	K3	2.621	5.646	5.313	5.313	5.313	2.621	5.313	5.646	4.309	4.642	3.302
Max	K4	7	4.309	6.316	4	4	1.817	5.944	7	4	7	3.302
Max	K5	7	5.646	5.313	7	4	4.642	4	5.646	4.642	5.313	3.634
Max	K6	7	5.313	5.646	3.302	5.313	1.817	5.313	7	4	4	4.642
Max	K7	6.649	4.309	5	5.518	6.649	4	5.313	6.649	3.302	4	5
Max	K8	6	4.309	5.313	4.579	6	4	5.646	5.809	3.302	3.915	3
Max	K9	7	5	6	5	7	4.932	5.646	6.257	4.309	4	4
Max	K10	6.316	5.646	2.884	3.107	6	4	6	6.316	4.932	3.634	2.289
Max	K11	6.316	4.642	4.642	4	6.257	3.302	4	6.316	5.646	5	2.621
Max	K12	6.316	5	2.621	1.587	6.316	2	4	5.313	4	3.634	1.587
Min	K13	1.817	2.289	2.621	3	5	1.817	6.316	6.649	3.915	2.289	2.289
Min	K14	1.817	2.621	2.289	2	6.649	2	5.646	6.316	4.309	2.289	1.817
Max	K15	6.649	3	1.587	3	5.313	2.289	6.649	5.944	4.642	4.642	1.587
Max	K16	6	6	5	5	5.944	2.621	5.646	5.313	5.313	2	2.289
Max	K17	5.646	5	4.642	5.646	4.579	4.642	5.646	5.241	4.932	4.217	3.302
Min	K18	1.817	6	3	4	5	1.817	6.649	6.649	2.289	4.642	2.621
Min	K19	3.915	4.642	4	4.309	6.649	5	4.932	6.316	6	4.309	3.915
Min	K20	1.817	5.313	4.642	1.817	6.649	3.302	4.642	5.646	6	4.309	3.915

Table 13. Grey relational coefficient matrix.

Criterion Side	Criteria	Alternatives									
		A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
Min	K1	0.333	0.504	0.538	0.63	1	0.497	0.352	0.497	0.497	0.861
Min	K2	0.362	0.416	0.454	0.416	0.555	0.624	0.333	1	0.382	0.738
Min	K3	0.333	0.36	0.36	0.36	1	0.36	0.333	0.473	0.428	0.69
Max	K4	0.491	0.791	0.463	0.463	0.333	0.71	1	0.463	1	0.412
Max	K5	0.554	0.499	1	0.359	0.416	0.359	0.554	0.416	0.499	0.333
Max	K6	0.606	0.657	0.412	0.606	0.333	0.606	1	0.463	0.463	0.524
Max	K7	0.417	0.504	0.597	1	0.387	0.556	1	0.333	0.387	0.504
Max	K8	0.47	0.686	0.513	1	0.429	0.809	0.887	0.357	0.418	0.333
Max	K9	0.429	0.6	0.429	1	0.42	0.526	0.669	0.358	0.333	0.333
Max	K10	0.75	0.37	0.386	0.864	0.465	0.864	1	0.593	0.429	0.333
Max	K11	0.525	0.525	0.444	0.969	0.38	0.444	1	0.734	0.584	0.333
Max	K12	0.642	0.39	0.333	1	0.354	0.505	0.702	0.505	0.469	0.333
Min	K13	0.836	0.75	0.671	0.432	1	0.349	0.333	0.535	0.836	0.836
Min	K14	0.75	0.836	0.93	0.333	0.93	0.387	0.349	0.492	0.836	1
Max	K15	0.41	0.333	0.41	0.654	0.367	1	0.782	0.558	0.558	0.333
Max	K16	1	0.667	0.667	0.973	0.372	0.85	0.744	0.744	0.333	0.35
Max	K17	0.645	0.538	1	0.523	0.538	1	0.743	0.622	0.451	0.333
Min	K18	0.366	0.671	0.525	0.432	1	0.333	0.333	0.836	0.461	0.75
Min	K19	0.653	0.941	0.776	0.333	0.558	0.573	0.363	0.396	0.776	1
Min	K20	0.409	0.461	1	0.333	0.619	0.461	0.387	0.366	0.492	0.535

Table 14. Equal Levels of Importance and Different Levels of Importance / Corresponding Rankings obtained by using the GRA for each one of alternatives.

Alternatives	Equal Levels of Importance / Ranking	Equal Levels of Importance / Ranking
A1	0.5491 / 7	0.5663 / 6
A2	0.5750 / 5	0.5933 / 5
A3	0.5953 / 3	0.6137 / 3
A4	0.6341 / 2	0.6323 / 2
A5	0.5729 / 6	0.5635 / 7
A6	0.5907 / 4	0.6058 / 4
A7	0.6433 / 1	0.6619 / 1
A8	0.5371 / 9	0.5384 / 10
A9	0.5491 / 10	0.5447 / 9
A10	0.5750 / 8	0.5458 / 8

indicates that the impact of this technology on circular supply chain performance is quite strong. The other two technologies ranked at the top were A4 and A3. The high ranking of these technologies reveals that they are strategic priorities within the scope of I4.0. However, A9 and A10 solutions received low correlation scores in both scenarios and remained at the bottom of the ranking. This suggests that these technologies performed relatively weakly according to the criteria used in the analysis.

D. MAIRCA findings

The steps of applying the MAIRCA method are defined as follows:

Step 1. Evaluations were first obtained from experts within the linguistic scale scope of Table 4, and a decision matrix was created. This matrix forms the basis of the multi-criteria evaluation process and provides the data infrastructure to be used in subsequent calculations. Then, the probability of each alternative being selected is defined. Due to the nature of the MAIRCA method, these probabilities are assumed to be equal and are calculated as 0.1, using (30).

Step 2. The theoretical evaluation matrix is obtained by multiplying the criterion weights in Table 8, previously obtained using the LOPCOW, by the probability of preference as shown in (31). This represents the expected (ideal) performance of each alternative according to each criterion. Subsequently, the actual evaluation matrix is obtained using (32) for useful criteria and (33) for useless criteria. The resulting matrix is given Table 15.

Table 15. True rating matrix.

Criterion Side	Criteria	Alternatives A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	X_{ij}^{+}	X_{ij}^{-}
Min	K1	0	0.003	0.003	0.004	0.006	0.003	0	0.003	0.003	0.005	7.319	2.621
Min	K2	0.001	0.001	0.002	0.001	0.003	0.003	0	0.004	0.001	0.004	5.646	2.289
Min	K3	0	0	0	0	0.002	0	0	0.001	0.001	0.002	5.646	2.621
Max	K4	0.003	0.005	0.002	0.002	0	0.005	0.006	0.002	0.006	0.002	7	1.817
Max	K5	0.003	0.002	0.004	0	0.001	0	0.003	0.001	0.002	0	7	3.634
Max	K6	0.005	0.005	0.002	0.005	0	0.005	0.007	0.003	0.003	0.004	7	1.817
Max	K7	0.002	0.003	0.003	0.005	0.001	0.003	0.005	0	0.001	0.003	6.649	3.302
Max	K8	0.002	0.004	0.003	0.005	0.002	0.004	0.005	0.001	0.002	0	6	3
Max	K9	0.001	0.003	0.001	0.004	0.001	0.002	0.003	0	0	0	7	4
Max	K10	0.004	0.001	0.001	0.005	0.002	0.005	0.005	0.003	0.002	0	6.316	2.289
Max	K11	0.003	0.003	0.002	0.006	0.001	0.002	0.006	0.005	0.004	0	6.316	2.621
Max	K12	0.003	0.001	0	0.004	0	0.002	0.003	0.002	0.002	0	6.316	1.587
Min	K13	0.005	0.005	0.004	0.002	0.006	0	0	0.003	0.005	0.005	6.649	1.817
Min	K14	0.004	0.005	0.005	0	0.005	0.001	0	0.003	0.005	0.005	6.649	1.817
Max	K15	0.001	0	0.001	0.003	0.001	0.004	0.003	0.002	0.002	0	6.649	1.587
Max	K16	0.005	0.004	0.004	0.005	0.001	0.005	0.004	0.004	0	0	6	2
Max	K17	0.005	0.004	0.007	0.004	0.004	0.007	0.006	0.005	0.003	0	5.646	3.302
Min	K18	0.001	0.003	0.002	0.001	0.004	0	0	0.004	0.002	0.004	6.649	1.817
Min	K19	0.004	0.006	0.005	0	0.003	0.004	0.001	0.001	0.005	0.006	6.649	3.915
Min	K20	0.001	0.002	0.005	0	0.003	0.002	0.001	0.001	0.002	0.003	6.649	1.817

Step 3. The gap matrix is created using (34). Evaluation scores are calculated using (36) to determine the overall performance (Q_i) level of each alternative. These values are shown in Table 16.

Step 4. As a result of the calculations performed, a ranking was obtained by evaluating the total difference values for each option. This ranking was created based on the proximity of the alternatives to the ideal situation. This ranking is also shown in Table 16. The alternative with the lowest difference was placed first as the most advantageous option. The other alternatives were ranked in ascending order based on their difference values. This approach ensures that the most suitable option is systematically determined in the decision-making process.

At the end of the evaluation process, the technology that achieved the highest success score was A2. Following closely behind, A3 and A7 were among the other prominent technologies. According to the ranking obtained, approaches based on data processing and digital infrastructure showed higher compatibility. A7 and A4 were in the middle of the list, while technologies such as A8, A9, and A10 were ranked lower. This ranking reveals that some technologies had a more dominant impact in terms of evaluation criteria.

E. Comparison of results and discussion

The rankings obtained using the MARCOS, GRA (Different Importance Levels), and MAIRCA methods are shown in Table 17. The GRA results based on "different importance levels" were used in the comparative study. The study guarantees that the particular impact of each circularity KPI is appropriately reflected in the final technological prioritization by employing the various importance levels of GRA results rather than an equal-importance approach, offering a stronger foundation for comparison with the MARCOS and MAIRCA models.

In this study, the MAIRCA, MARCOS, and GRA methods were used together to analyze alternatives from different perspectives when evaluating I4.0 technologies. The use of multiple methods in MCDM problems contributes to the comparison of results, thereby increasing their reliability. The selected methods have distinct characteristics. The MAIRCA method evaluates alternatives based on the deviation between their theoretical and actual performance and identifies the alternative with the lowest deviation as the best option. The MARCOS method, on the other hand, ranks alternatives according to relative utility functions by positioning them relative to an ideal and anti-ideal solution. The ranking is based on a compromise solution that seeks maximum benefit. In contrast, the GIA method provides effective results in uncertain situations by measuring the relational proximity between alternatives and a reference series. The primary reason for using these methods together is that they represent different analytical approaches. By presenting deviation-based (MAIRCA), ideal-anti-ideal-based (MARCOS), and relational proximity-based (GIA) evaluations, complementary and comparable results have been obtained.

Table 16. Q_i values and ranking alternatives using the MAIRCA.

Alternatives	Q_i	Ranking
A1	0.0470	6
A2	0.0411	1
A3	0.0417	2
A4	0.0435	5
A5	0.0533	9
A6	0.0428	4
A7	0.0422	3
A8	0.0508	7
A9	0.0510	8
A10	0.0587	10

When considering the rankings obtained through three different MCDM, Automation and Intelligent Production Systems ranked highest on average and were determined to be the most suitable alternative. Robotics and AI followed this result, demonstrating strong performance, particularly in the GRA and MARCOS methods and ranking second. Big Data and Data Analytics ranked third in the overall evaluation, placing high in almost all methods. Cloud Computing remained in fourth place, despite its high rankings in the MAIRCA and MARCOS methods, as it ranked lower in other methods. Cyber-Physical Systems ranked fifth with a balanced but moderate performance. On the other hand, IoT ranked sixth in the overall average, while DT Technology was ranked seventh. 3D Printing and IoS generally ranked lower on the list, placing eighth and ninth, respectively. Blockchain, which received the lowest scores across all methods, ranked tenth, emerging as the weakest alternative.

A7 technology plays a critical role in operational efficiency in the short term and strategic transformation in the long term. It improves process performance by minimizing human error. At the same time, it creates a structure that enables other digital components such as IoT, big data, cloud computing, and cyber-physical systems to function. Therefore, investment in this technology is an investment in the entire digital transformation ecosystem. Furthermore, automation systems that reduce energy consumption, waste, and carbon emissions also support sustainable production goals. On the other hand, A4 technology is a critical component in the automation of production processes. Robotic systems ensure the continuity of production processes by performing repetitive tasks at high speed, accurately, without

Table 17. Comparison of results.

Ranking	MARCOS	GRA (Different Importance Level)	MAIRCA
1	A7. Automation and Smart Manufacturing Systems	A7. Automation and Smart Manufacturing Systems	A2. Cloud Computing
2	A4. Robotics and Artificial Intelligence	A4. Robotics and Artificial Intelligence	A3. Big Data and Data Analytics
3	A2. Cloud Computing	A3. Big Data and Data Analytics	A7. Automation and Smart Manufacturing Systems
4	A6. Cyber-Physical Systems	A6. Cyber-Physical Systems	A6. Cyber-Physical Systems
5	A3. Big Data and Data Analytics	A2. Cloud Computing	A4. Robotics and Artificial Intelligence
6	A1. IoT	A1. IoT	A1. IoT
7	A8. Digital Twin Technology	A5. 3D Printing	A8. Digital Twin Technology
8	A9. IoS	A10. Blockchain	A9. IoS
9	A5. 3D Printing	A9. IoS	A5. 3D Printing
10	A10. Blockchain	A8. Digital Twin Technology	A10. Blockchain

errors, and in a manner that ensures workplace safety. They also contribute to human-robot collaboration, reducing the physical burden on workers, improving ergonomic conditions, and enhancing workplace safety. They optimize processes by learning, predicting, and analyzing the data obtained from the systems. They work in direct interaction with A7 and A3 technologies. Investing in A3 technology is one of the most strategic steps in digital transformation. This technology enables the design of decision support systems by transforming data into meaningful information. Thanks to big data analytics, companies can make data-driven decisions in critical areas such as demand forecasting, process optimization, maintenance planning, and quality management. Furthermore, by integrating with A2 and A6 technologies, it enables end-to-end traceability throughout the supply chain. Although the alternative rankings may vary slightly for each method, it is important to note that the technologies work in synergy with each other.

A7 ranked highest in both MARCOS and GRA methods, making it the most critical technology for CSC performance. This is due to automation increasing operational efficiency, minimizing human error, and supporting sustainability goals by reducing energy consumption and waste. It also provides a fundamental ecosystem upon which other digital components, such as IoT and big data, can be built. On the other hand, A10 technology has shown the lowest performance in all analyses and scenarios. This can be attributed to the technological infrastructure challenges and investment requirements associated with blockchain integration. While automation systems have long existed in industry, Blockchain technology is still in its development phase for supply chain and logistics processes. Furthermore, when considering the most effective economic criteria, such as K17, Blockchain's status as a new technology and its high investment cost have caused it to lag.

An examination of the comparative analysis results in Table 17 reveals a shift in the top-ranked alternative. When considering the methodological structure of the approaches, it becomes evident that the primary reason A2 emerges as the best alternative in MAIRCA, while A7 leads in MARCOS and GRA, lies in the mathematical orientation of the algorithms. MARCOS is a benefit-based method that prioritizes alternatives by maximizing their distance from the anti-ideal solution. A7's superiority here indicates that it possesses the most robust compromise profile. In contrast, MAIRCA focuses on minimizing the total distance between theoretical and empirical evaluation scores. A2's rise in MAIRCA indicates that this technology has the smallest cumulative performance gap across all criteria. The GRA method, on the other hand, evaluates alternatives based on the shape of their data series relative to an ideal series. A7's top ranking in GRA indicates that A7 is the alternative whose rises and falls across the criteria most closely resembles the values of the reference series defined as ideal. In other words, A7 is the technology with the most balanced profile and the one that most closely parallels the ideal profile. In conclusion, the evaluations based on the calculation approach aimed at the ideal outcome indicate that the A7 alternative is the most significant. Similar results hold for the alternatives in other rankings as well. These variations do not indicate inconsistency; rather, they provide multifaceted validation. The consistent ranking of A6 in the 4th place and A1 in the 6th place across all methods demonstrates the stability of the underlying data structure and indicates that the fundamental variations are a result of the specific mathematical calculations applied by each MCDM tool.

F. Sensitivity Analysis

Sensitivity analysis is a crucial step in MCDM studies for assessing the reliability of the results and examining the model's behavior under different conditions. It enables the assessment of how changes in criterion weights affect the ranking of alternatives and helps identify which variables the model is most sensitive to. In this respect, sensitivity analysis contributes to testing the consistency and robustness of the decision-making process [73], [74]. Moreover, it allows examination of model outputs across different scenarios and provides insights into potential rank-reversal situations. In this study, a sensitivity analysis was conducted to evaluate the effect of changes in criterion weights on the ranking of alternatives. Accordingly, five different scenarios were developed. In scenario 1, the weights of the criteria with the highest and lowest weights obtained using LOPCOW were swapped. In scenario 2, the weights of the criterion with the highest weight and the criterion with the second lowest weight were rearranged. In scenario 3, the weights of the criterion with the highest weight and the criterion with the third lowest weight were changed. In scenario 4, changes were made to the weights of the criterion with the highest weight and the criterion with the fourth lowest weight. Finally, in scenario 5, the weights of the criterion with the highest weight and the criterion with the fifth lowest weight were changed, completing the analysis. Radar charts were created for the scenarios using the MCDM methods selected for the 3 alternative rankings, and evaluations and interpretations were made. The results of this analysis provide a comprehensive understanding of the stability of the model and the extent to which changes in criterion weights influence the final decision outcomes. The MARCOS method was applied according to five separate scenarios, and the changes in the obtained alternative rankings are presented visually in Fig. 3.

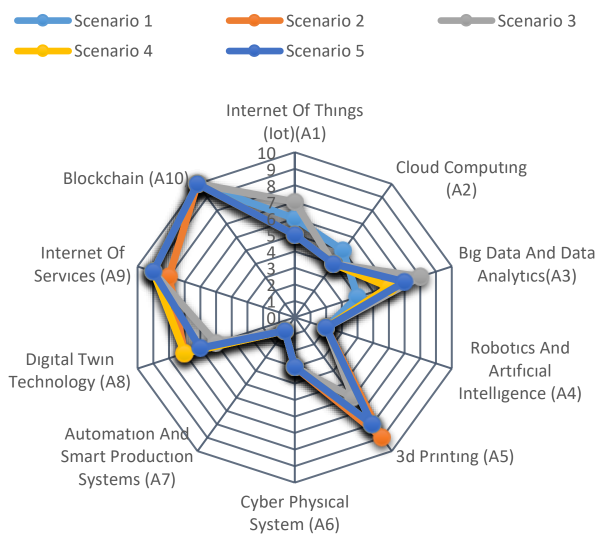


Fig. 3. MARCOS method scenario analysis radar chart.

When analyzing the results, the A7 technology ranked first in all scenarios. This finding demonstrates that technology remains a viable choice even under different weighting criteria and delivers consistent performance. On the other hand, "Blockchain" technology ranked last in all scenarios and was the alternative with the lowest performance in terms of evaluation criteria. This situation shows that Blockchain is weak within the scope of the current set of criteria and is unlikely to be a priority choice. It was observed that some technology alternatives had different rankings across scenarios. The A3 technology ranked fourth in the first scenario but dropped to sixth place in the third scenario. Such ranking changes indicate that these alternatives are more sensitive to fluctuations in criterion weights. Some alternatives, such as A1, A8, and A2 are positioned in the middle ranks across scenarios and do not exhibit significant stability or sensitivity. Overall, this sensitivity analysis stands out as an important tool for determining which technologies are more stable and which are more variable under different evaluation conditions. The GRA method was applied according to five separate scenarios, and the changes in the obtained alternative rankings are presented visually in Fig. 4.

According to the scenario analysis results, the A7 technology was found to rank first in all scenarios. This finding demonstrates that this technology showed a high level of stability against the evaluation criteria and is a priority choice for decision-makers. Similarly, A4 technology also ranked second in each scenario, emerging as a consistent and high-priority alternative. Such consistent rankings show that these technologies can maintain their advantages even under different criteria weights. In contrast, the A9 technology ranked 9th or 10th in each scenario, making it one of the alternatives with the lowest performance in the evaluation. Similarly, A10 has generally remained in the lower ranks and demonstrated a relatively low level of preference. On the other hand, differences in the rankings of some technologies across scenarios have been observed. For example, A8 ranked eighth in the first scenario, fell to tenth in the second scenario, and rose back to eighth in the fourth and fifth scenarios. Such fluctuations indicate that these technologies are more sensitive to changes in the weighting of decision criteria.

The changes in the alternative rankings obtained by applying the MAIRCA method to five different scenarios are presented visually in Fig. 5. The findings show that the A7 alternative ranks among the top three in many scenarios, particularly standing out as a strong preference for decision-makers by ranking first in the first scenario. Similarly, A4 technology was generally ranked highly; it rose to first place in the third and fifth scenarios, demonstrating a significant advantage under certain criteria weight combinations. On the other hand, A10 technology ranked last in

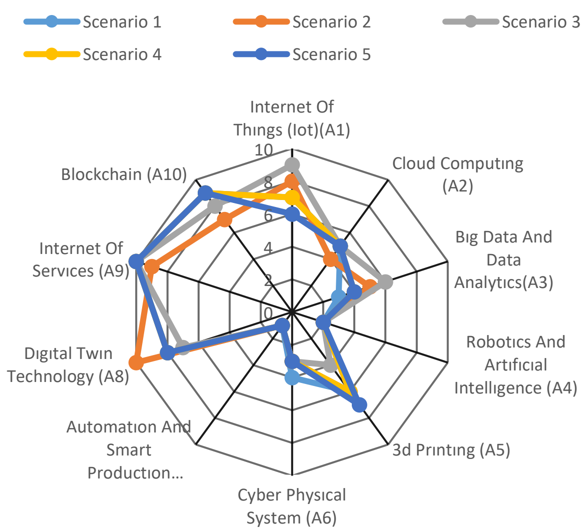


Fig. 4. GRA method scenario analysis radar chart.

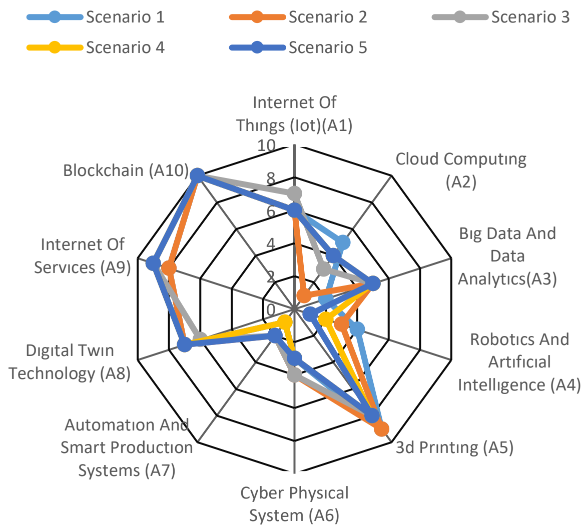


Fig. 5. MAIRCA method scenario analysis radar chart.

each scenario and thus stood out as the alternative with the lowest performance in the analysis. A9 technology similarly ranked ninth in most scenarios, making it another low-performing option. Some alternatives were observed to have a relatively more stable ranking structure. For example, A8 ranked sixth or seventh in most scenarios, indicating that this technology is less sensitive to changes in criterion weights. Overall, this analysis conducted using the MAIRCA method reveals under which conditions technological alternatives become more advantageous and in which situations their rankings fluctuate.

IV. CONCLUSION and FUTURE RESEARCH

Within the scope of this study, the relationship between I4.0 technologies and circular supply chain performance indicators has been comprehensively analyzed using MCDM methods. In the first phase of the research, the concepts of I4.0 and circular supply chain were examined in detail, and the strategic advantages that could arise for businesses because of the integration of these two structures were discussed. As a result of literature reviews, ten different I4.0 technologies were identified for use in performance evaluations, along with twenty performance indicators to analyze these technologies. Subsequently, MCDM methods were utilized to analyze alternative technologies based on these criteria. The evaluation process benefited from the opinions of three experienced experts. The data obtained from the experts was compiled into a common decision matrix and integrated for use in the analysis. The analysis process began with the LOPCOW method, which calculates criterion weights. The weights obtained were then integrated into the MARCOS, GRA, and MAIRCA methods to rank the alternative technologies. An analysis of the criterion weighting results obtained using LOPCOW reveals that the Operating Cost Savings criterion (K17) has the highest priority, highlighting the decisive role of economic sustainability in a circular supply chain structure. Indeed, the literature emphasizes that factors such as optimizing resource use, reducing waste, and developing cost-effective processes directly enhance business performance and play a critical role in decision-makers' prioritization processes [40]. Furthermore, considering that KPIs serve as an effective guiding tool in decision-making processes and that economic indicators become more dominant in crisis and uncertainty environments, the reason why K17 ranks first in expert evaluations becomes clear. The Supplier Performance Ratio (K6), which ranks second, demonstrates that the overall success of the supply chain is largely dependent on supplier efficiency. Suppliers' efficient use of resources and ability to ensure uninterrupted flow are key factors in enhancing supply chain resilience [34]. In this context, it is an expected outcome that a high-performing supplier structure ranks highly, as it supports both operational efficiency and cost advantages. The Delivery Accuracy Rate (K4), ranked third, is a critical performance indicator in terms of customer satisfaction and service quality. Consistent with the finding that delivery accuracy and on-time delivery are directly linked to operational success, it has emerged as the third most important criterion [27]. However, the fact that the criteria with the lowest weights—Reuse (Repair) Rate (K12) and Work Rate Supporting Sustainable Production (K9)—were rated low indicates that, despite their importance for the circular economy, these criteria take a back seat in short-term performance evaluations because they primarily yield long-term benefits. Additionally, the fact that social sustainability indicators are more abstract and difficult to measure also explains this lower prioritization. Similarly, the fact that Order Delivery Time (K3) ranks lowest in priority reveals that, among time-related criteria, indicators directly impacting customer experience (such as delivery accuracy) are viewed as more critical. Overall, the findings indicate that economic and operational criteria dominate in terms of short-term performance, while social and environmental criteria, despite their long-term strategic importance, are given lower priority. When the results are assessed from a managerial view, it reveals that transitioning to a circular supply chain is not only a sustainability effort but also a strategic cost management necessity. The prominence of cost savings in operating operations indicates that decision-makers are prioritizing digitalization to reduce resource waste and financial inefficiencies. Therefore, managers should view investments in the Fourth Industrial Revolution as a long-term safeguard against rising raw material costs and waste disposal costs in linear systems.

In the assessment of alternatives using the MARCOS method, the technology with the highest performance was Automation and Smart Production Systems. This was followed by Robotics and AI in second place and Cloud Computing in third place. Fourth place went to Cyber-Physical Systems, fifth to Big Data and Data Analytics, sixth to the IoT, seventh to DT Technology, eighth to the IoS, ninth to 3D Printing, and last to Blockchain.

The GRA method was applied according to two different levels of importance. In the analysis conducted according to different levels of importance, Automation and Smart Production Systems were again in first place, followed by Robotics and AI in second place, and Big Data and Data Analytics in third place. This was followed by Cyber-Physical Systems, Cloud Computing, IoT, 3D Printing, Blockchain, IoS, and finally DT Technology. In the analysis based on equal importance levels, Automation and Smart Production Systems, Robotics and AI, and Big Data and Data Analytics again ranked in the top three, followed by Cyber-Physical Systems, Cloud Computing, 3D Printing, IoT, Blockchain, DT Technology, and IoS. Since LOPCOW measures the variance in the data, different levels of importance were used for comparison to ensure that the evaluation was conducted in the same manner. According to the ranking obtained using the MAIRCA method, Cloud Computing was determined to be the most successful technology. Big Data and Data Analytics ranked second, followed by Automation and Intelligent Production Systems in third place, fourth place is Cyber-Physical Systems, fifth place is Robotics and AI, sixth place is the IoT, seventh place is DT Technology, eighth place is the IoS, ninth place is 3D Printing, and tenth place is Blockchain. When comparing the results of all methods, no significant differences were observed in the rankings. The theoretical contribution of this integrated framework lies in its ability to capture the diverse dimensions of the technological assessment space. While Automation and Intelligent Manufacturing Systems consistently lead due to their relational alignment with ideal performance metrics, the rise of Cloud Computing in the MAIRCA rankings highlights its role in minimizing productivity gaps. This demonstrates that a hybrid MCDM approach, transcending a single ranking logic, is necessary to capture the multifaceted nature of circular economy transitions where technological "alignment" (GRA) and "minimizing the gap" (MAIRCA) are equally vital. In particular, Automation and Smart Production Systems technology ranked high in almost every method, standing out for its contributions to the circular supply chain. Robotics and AI technology also consistently ranked high, once again demonstrating its importance in this field. Big Data and Data Analytics performed highly in certain scenarios and generally ranked high. However, Blockchain and IoS technologies generally ranked low across all methods. Some technologies, such as DT Technology and 3D Printing, mostly ranked in the middle, showing noticeable ranking changes in some methods.

To test the reliability of the research, sensitivity analysis was performed and various changes were applied to the criterion weights. As a result of these analyses, it was observed that the technologies ranked at the top did not undergo significant changes in the ranking. This finding demonstrates that the results obtained are robust and consistent. In conclusion, the integration of I4.0 technologies into the circular supply chain offers important opportunities in terms of sustainability, flexibility, and operational efficiency. This study aims to contribute to academic literature and provide strategic guidance to businesses by enabling a comparative assessment of these technologies.

It should be mentioned that the assessments of three experts with significant knowledge of the topic provided a framework for the study's conclusions. Although expert perspectives offer insightful information, the results may not be as broadly applicable due to the small number of experts. It would be possible to compare results and strengthen the findings' robustness if a broader and more varied group of experts were included. Increasing the number of specialists would help achieve more thorough and broadly applicable conclusions in many scenarios, in addition to validating the current findings. Future research could involve comparing other MCDM techniques, recalculating the suggested methodology under fuzzy set extensions, assessing the outcomes, and determining how resilient the results are. Furthermore, future studies could expand the theoretical framework by incorporating the Industry 5.0 paradigm, particularly by considering the human-centered and resilient dimensions of circular supply chains. Examining the dynamic interactions between these technologies using System Dynamics or Agent-Based Modeling could provide deeper insights into the long-term progress of digital-circular integration.

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