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Analyzing the Smart Industry Readiness Index in Adopting Industry 4.0 Technologies

Fawaz M. Abdullah [1,2,*] and Abdulrahman M. Al-Ahmari [1,2]

[1] Industrial Engineering Department, College of Engineering, King Saud University, P.O. Box 800, Riyadh 11421, Saudi Arabia
[2] Raytheon Chair for Systems Engineering (RCSE Chair), King Saud University, P.O. Box 800, Riyadh 11421, Saudi Arabia
* Correspondence: fmuthanna@ksu.edu.sa; Tel.: +966-553989419

Abstract

Industry 4.0 (I4.0) promises that technological advances are happening at an accelerating rate, which is pushing all industries to undergo digital transformation to boost competitiveness, productivity, and business efficiency. As industrial companies transition to Industry 4.0, one of the maturity models that helps them identify opportunities is the Smart Industry Readiness Index (SIRI). SIRI is in line with other international manufacturing initiatives and has the potential to become a global standard for the manufacturing sector's future. To achieve market competitiveness, smart manufacturing requires the end-to-end integration of Industry 4.0 technologies and SIRI. The successful implementation of such a comprehensive integration depends on carefully selecting the I4.0 technologies to conform to industry requirements. The Influences of I4.0 technologies on SIRI are not clearly outlined in any of the earlier research. Thus, employing a dependable Multi-Criteria Decision Making (MCDM) methodology using fuzzy TOPSIS, this article aims to analyze the influence of Industry 4.0 technologies on SIRI from the perspectives of both academic and industry experts. Expert opinions were gathered on the relationship between SIRI and I4.0 technologies. TOPSIS utilizes fuzzy theory to address the ambiguity and uncertainty inherent in human judgment. The findings showed that the best I4.0 technology for SIRI is the cyber-physical system (CPS).

Keywords: digitalization; Industry 4.0 technologies; Smart Industry Readiness Index; Fuzzy TOPSIS

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1. Introduction

Manufacturers today face a growing demand for a wider variety of products (i.e., individualized), smaller lot sizes, and erratic market demands. Manufacturers must adopt new theories and technologies to optimize energy and resource utilization, improve product quality, and respond promptly to changes. Industry 4.0 technologies have introduced a new manufacturing trend in sectors that strive for optimal output through efficient use of resources. One could argue that "smart manufacturing" or "digital manufacturing" is the foundation of Industry 4.0, which enables businesses to carry out adaptable manufacturing processes with mass customization [1,2]. In the meantime, the Fifth Industrial Revolution, also known as Industry 5.0, represents a new phase of industrialization where people collaborate with robotics and cutting-edge technology to enhance work processes. It is predicated on the finding or presumption that I4.0 places more emphasis on digitalization

and related technologies to increase production flexibility and efficiency than it does on the core principles of sustainability and social justice [3,4].

Smart manufacturing is a new generation of manufacturing that has recently been promoted by international organizations [5]. It is distinguished by self-sufficient production processes that react to demand through improved data processing, sensing, and decision-making technologies. To improve every facet of manufacturing, smart manufacturing aims to convert data gathered during the product lifecycle into actionable manufacturing information. Consequently, Industry 4.0 is a revolutionary wave that meets customer demands effectively and swiftly. It began with the intention of creating products that reflected consumer needs through effective manufacturing procedures; designers might refer to this idea as the "flexible integration of the global value chain." [6,7]. It aims to create flexible workflows and efficient, affordable production to create customized, high-quality products.

Personalized, intelligent, effective, affordable, and adaptable products are made possible by I4.0. As a result of automation and data exchange, Industry 4.0 helps make manufacturing more digital [8]. It highlights the significance of cyber-physical systems (CPS) and smart technologies, which enable the integration of factories, machinery, and business processes, and are characterized by remarkable capabilities such as autonomous information sharing, action initiation, decision-making, and independent control [9]. Through the use of CPS and the Internet of Things, Industry 4.0 aims to integrate and connect the real and physical worlds with the digital/virtual worlds, where intelligent devices constantly interact and communicate [10]. I4.0 enhances industrial capacity by simplifying the production of high-quality goods, delivered quickly, affordably, and safely [11]. Smaller sensors, smarter gadgets, faster computers, and more reasonably priced data transmission and storage make it feasible to connect and learn from machines and objects, making them smarter [12].

Highly advanced electronics, IT, and automation, as well as digitization processes, are characteristics of Industry 4.0 [13]. From the perspective of production and service management, I4.0 concentrates on developing intelligent and communicative systems, including machine-to-machine and human–machine interactions, to manage data flow from intelligent and dispersed system interactions [14]. Additional emerging technologies that integrate the physical, digital, and biological worlds and have an impact on all fields, economies, and organizations include the Internet of Things, cloud manufacturing, big data, automation, industrial robotics, additive manufacturing, augmented reality, modeling and simulation, and cybersecurity [8].

Adopting cutting-edge and Industry 4.0 technologies can be challenging for organizations due to the complexity and cost associated with Industry 5.0's endeavors to address critical issues such as economic, social, and technological challenges, as well as the integration between Industry 4.0 and Industry 5.0. Greater integration between technology and human-centric models is expected to produce more sustainable and ecologically friendly products. Technological, sociological, and economic challenges are at the forefront of manufacturing technologies [4].

Industrial companies can use the Smart Industry Readiness Index (SIRI), one of the I4.0 maturity models, to find opportunities as they transition to Industry 4.0. SIRI is potentially one of the global standards for the future of I4.0 and is closely correlated with other global manufacturing initiatives [15]. The Singapore Smart Industry Readiness Index (SIRI) was jointly unveiled in November 2017 by the Singapore Economic Development Board (EDB) and the global testing, inspection, certification, and training company TÜV SÜD. SIRI was created using the Bersin model for human capital development and the core of the I4.0 Maturity Index [16]. SIRI was created as a comprehensive tool to assist industrial

businesses in leveraging Industry 4.0. It has the potential to become the global standard for manufacturing in the future, regardless of the type of business, its size, or the industry it operates in, and it is closely correlated with other global manufacturing initiatives [15].

The complexity of the manufacturing process is making it more and more crucial for manufacturers to make effective decisions. Consequently, Multi-Criteria Decision Making (MCDM) approaches can significantly reduce the complexity of the problem in a fuzzy ecosystem [17–19]. For the problem of ranking alternatives from most important to least important, the TOPSIS method is well-known. The requirement that the preferred option is the one that is closer to the ideal positive solution and the one that is most distant from the perfect negative solution is what defines TOPSIS. Therefore, the resolution that maximizes benefit while minimizing expense is the best one. The negative ideal solution, on the other hand, contains the worst values conceivable, while the ideal solution includes the most significant values conceivable for each criterion [20]. One of TOPSIS's primary benefits is that it uses an infinite quantity of data for each indication to rank options according to their influence [21].

TOPSIS is frequently used due to its ease of use and capacity to produce results that are easy to understand. Several key elements are among the method's benefits. Decision-makers with a variety of technical backgrounds can use the technique because it is relatively straightforward to implement. Users can see how close each alternative is to the ideal solution thanks to the TOPSIS method's straightforward and easy-to-understand results. This approach can handle both quantitative and qualitative criteria, as well as other types of data.

Additionally adaptable, TOPSIS can be applied in various domains, including engineering, finance, management, and others. It offers a methodical and uniform way to assess and contrast intricate options using a variety of criteria, many of which have varying weights of importance. Additionally, TOPSIS provides decision makers with a comprehensive and balanced view by enabling them to consider how close each alternative is to the ideal solution—both the most desirable (positive ideal) and the least desirable (negative ideal). Third, TOPSIS is a versatile tool that can be applied in various domains, including business, engineering, management, and others, due to its ability to handle both qualitative and quantitative data. Fourth, TOPSIS facilitates communication and decision justification with interested parties by generating solutions that are easy to comprehend and interpret. TOPSIS facilitates the multicriteria decision-making process by improving objectivity, transparency, and accuracy [22,23].

To achieve market competitiveness, this article offered an MCDM model for ranking I4.0 technologies. A number of factors, such as planned and limited resources, static routing, a lack of connectivity, autonomous control, and isolated information, make the traditional production system unsustainable in the enterprise's current state. Businesses now face additional challenges as a result of globalization, including a more complex and competitive marketplace, a volatile and hazardous trading environment, and shifting consumer expectations. Businesses must give technology that affects SIRI top priority if they want to maintain a competitive edge. Based on the literature review, none of the previous studies have clarified the influences of I4.0 technologies on SIRI. Enhancing the competitiveness and quality growth of the industrial production mode has become possible through the deep integration of digitalization with the broader economy [24,25]. This article aims to analyze the influence of the I4.0 technologies on SIRI. The main research contributions are listed below.

- In defining Industry 4.0 technologies in relation to manufacturing organizations, this research contributes to a deeper understanding of the Fourth Industrial Revolution.

- In terms of SIRI improvement, this article empirically examines the connection between I4.0 and SIRI.
- To counter global competition, manufacturing organizations can choose the right I4.0 technologies thanks to this research.

2. Research Methodology

A fuzzy MCDM approach is presented in this section to help decision-makers rank and assess the effects of I4.0 technologies on SIRI. By assigning essential Industry 4.0 concepts and technologies to three primary pillars—Process, Technology, and Organization, the connections between Industry 4.0 technologies and the Smart Industry Readiness Index (SIRI) are based on a framework that aids businesses in evaluating, comparing, and enhancing their digital transformation initiatives. The Key Linkages are as follows:

- With an emphasis on integrating cutting-edge technologies such as IoT, AI, robotics, and automation across business and manufacturing processes, SIRI is a structured tool for mapping readiness and guiding Industry 4.0 transformation.
- Businesses can customize their Industry 4.0 journeys with strategic, phased roadmaps created using the SIRI framework.
- To guarantee competitive and future-ready manufacturing, SIRI serves as a comprehensive guide for Industry 4.0 transformation, closely tying operational and process maturity to technological breakthroughs.

This article will examine SIRI, as described in Table 1 [15]. SIRI's comprehensive evaluation of digital maturity across three key dimensions—Process, Technology, and Organization—as well as 16 distinct subdimensions that address every important facet of Industry 4.0 transformation, makes it a widely accepted assessment tool. The comprehensive nature of these SIRI dimensions offers clear guidance for creating transformation roadmaps, evaluating maturity, and setting priorities for initiatives in manufacturing settings, even though there are not many studies that fully address them. Choosing SIRI guarantees a methodical, verified framework for identifying an organization's readiness gaps and strengths, which is essential for strategic decision-making regarding operational excellence and digitization.

Table 1. Smart Industry Readiness Index Dimensions.

SIRI	Dimensions	Rep.	Definition
Process	Vertical Integration	SIRI-1	Vertical integration is the process of creating a connected, end-to-end data thread within a facility by integrating systems and processes at all hierarchical levels of the automation pyramid.
	Horizontal Integration	SIRI-2	Enterprise processes are integrated horizontally with stakeholders along the value chain and throughout the organization.
	Integrated Product Lifecycle	SIRI-3	Integrated Product Cycle is the process of integrating people, processes, and systems throughout the product lifecycle, including design and development, engineering, production, customer use, service, and disposal. In this section, we will explore some of the more common questions that arise in the field of e-commerce, including how to use e-commerce in a sustainable manner.

Table 1. *Cont.*

SIRI	Dimensions	Rep.	Definition
Technology	Shop Floor Automation	SIRI-4	The use of technology to oversee, manage, and carry out the production and delivery of goods and services within the site where these activities are conducted is known as shop floor automation.
	Enterprise Automation	SIRI-5	Enterprise automation refers to the use of technology in the administrative work environment to monitor, control, and carry out processes. Demand planning, procurement, sales and marketing, and human resource management and planning are a few examples of these procedures.
	Facility Automation	SIRI-6	The application of technology to the physical building and/or premises where the production area is located, in order to monitor, control, and automate processes, is known as facility automation. These procedures cover the control of lighting, security, HVAC, and chiller systems, among others.
	Shop Floor Connectivity	SIRI-7	The process of connecting machinery, equipment, and computer-based systems to facilitate communication and smooth data exchange within the area where goods are produced and managed is known as shop floor connectivity.
	Enterprise Connectivity	SIRI-8	The interconnection of machinery, computers, and other equipment to facilitate communication and smooth data exchange within the facility where administrative tasks are performed is known as enterprise connectivity.
	Facility Connectivity	SIRI-9	The process of connecting machinery, equipment, and computer-based systems within the actual building and/or the plot of land where the production area is situated, in order to facilitate communication and smooth data exchange, is known as facility connectivity.
	Shop Floor Intelligence	SIRI-10	Shop floor intelligence refers to the processing and analysis of data in the area where goods are produced and managed, to optimize current procedures and develop new applications, goods, and services.
	Enterprise Intelligence	SIRI-11	The processing and analysis of data to develop new applications, goods, and services, as well as optimize current administrative procedures, is known as enterprise intelligence.
	Facility Intelligence	SIRI-12	The processing and analysis of data within the actual building and grounds where the production area is situated, in order to optimize current processes and develop new applications, goods, and services, is known as facility intelligence.

Table 1. *Cont.*

SIRI	Dimensions	Rep.	Definition
Organization	Workforce Learning & Development	SIRI-13	The system of procedures and initiatives known as "workforce learning and development," or "L&D," aims to enhance the workforce's competencies, abilities, and skills, ultimately achieving organizational excellence.
	Leadership Competency	SIRI-14	The ability of the management core to use the newest trends and technologies to maintain the organization's relevance and competitiveness is referred to as leadership competency.
	Inter- & Intra-Company Collaboration	SIRI-15	The process of cooperating with external partners and cross-functional teams to accomplish a common goal is known as intra- and inter-company collaboration.
	Strategy & Governance	SIRI-16	The creation and implementation of a plan of action to accomplish several long-term objectives is known as strategy and governance. To convert a vision into business value, it entails setting priorities, creating a roadmap, and creating a set of guidelines, procedures, and practices.

Industry 4.0 (I4.0) technologies are chosen based on how well they align with the SIRI framework. So, they are well-known, technologies are selected (the ten Pillars of I4.0) and have a record of revolutionizing various industrial sectors. It is imperative that the final choice guarantees that the technologies have a direct impact on the fundamental SIRI dimensions. This approach ensures that the technologies being examined are not just theoretical ideas but rather the most potent and pertinent facilitators of reaching maturity in a contemporary, intelligent industrial setting.

The I4.0 technologies on the SIRI evaluation network are displayed in Figure 1. The I4.0 revolution, on the other hand, encompasses "new technologies that combine the physical, digital, and biological worlds and have an impact on all disciplines, economies, and industries." Potentially increasing economic and organizational efficiency by orders of magnitude, these technologies could connect billions more individuals to the internet. According to the reported studies [26–31], the I4.0 technologies in relation to manufacturing organizations are described as follows:

- Internet of things (loT): Through the Internet of Things, physical objects can exchange information, coordinate decisions, and communicate with one another [32–34]. It creates a network of humans to humans and things to things. IoT applications in manufacturing systems reduce the size of product recalls, identify defective products early, modify product designs, and improve product performance.
- Cloud manufacturing (CM) is a business model that leverages the sharing of cloud-based manufacturing capabilities and resources. Cloud manufacturing is ideal for contemporary manufacturers due to its cloud-based software, web-based management dashboards, and cloud-based collaboration capabilities. Despite their disparate locations, distributed manufacturing resources can be integrated to form a scalable platform [35].
- Big Data and Analytics (BD): It is characterized by vast amounts of diverse data that are moving in real time, coming from a range of sources, and taking many different forms [36]. This system and technology demonstrate how companies can gain a competitive edge by discovering, processing, and analyzing vast amounts of diverse data [37].

- Automation and industrial robotics (AIR): AIR is undoubtedly increasing, especially in business and, to a greater extent, in daily life [27]. Advanced robot technology (gluing, coating, laser-based processes, precision assembly, and fiber material processing) will be required for manufacturing processes and services in rapidly growing industries (such as electronics, food, logistics, and the life sciences).
- Additive manufacturing (AM): In additive manufacturing (AM), materials are joined, usually layer by layer, to create objects from three-dimensional (3D) model data [38,39]. It reduces waste and streamlines on-demand manufacturing, mass customization, and production procedures. Additionally, producing close to the end user increases supply chain flexibility.
- Augmented reality (AR): Augmented Reality (AR) is a new method for displaying computer images in the real world [40]. Through the provision of information required for a particular task, augmented reality enhances human performance [41].
- Modeling and simulation (MS): Designing, implementing, testing, and controlling a manufacturing system in real time should be made easier by modeling and simulation technologies [42]. Saving money, reducing development time, and improving product quality are all benefits of modeling and simulation.
- Cyber-Physical Systems (CPS): These provide and consume internet-based data-access and data-processing services, and are systems of cooperating computational entities closely connected to the real world and its activities [43]. Increased efficiency and greater manufacturing flexibility are two key advantages of distributed manufacturing systems made possible by CPS [44].
- Cybersecurity (CS): Cybersecurity makes CS a new paradigm for extremely secure information systems that can be utilized in manufacturing across the entire IoT ecosystem. "Cybersecurity" (CS) is the umbrella term for the set of tools used to prevent, detect, and respond to hackers [45].
- Blockchain (BC): Blockchain is a technology that enables a specific industry to have a decentralized, transparent financial transaction platform. Transparency, process integrity, stability, and adaptability are the attributes of BC technology [46]. With BC technology, any digital knowledge can be shared. BC has been adopted by numerous industries, including design, manufacturing, banking, supply chain management, and social networks [46].

Based on the information provided in previous studies, the experts chosen for the article had more than 10 years of experience [47]. According to [48], Acceptable experts for the article are those who have at least ten years of experience working in academia, business, or both. The majority of the experts who selected manufacturing companies had experience with I4.0 technologies. Respondents in this article include CEOs, general managers, department heads, specialized engineers, academics, and professionals with at least ten years of experience in smart manufacturing associated with industrial organizations. Experts must possess a comprehensive understanding of manufacturing, with a focus on smart manufacturing.

Additionally, professionals need to be familiar with I4.0 technologies, whether theoretically or practically [49]. They were responsible for production and operations, as well as market strategy. For this reason, they have a good understanding of smart manufacturing. Likewise, scholars with doctorates and professors who have written reputable studies on smart manufacturing were selected as academic experts. These experts have experience working for manufacturing or consulting companies, so the data they provide via questionnaires is very trustworthy.

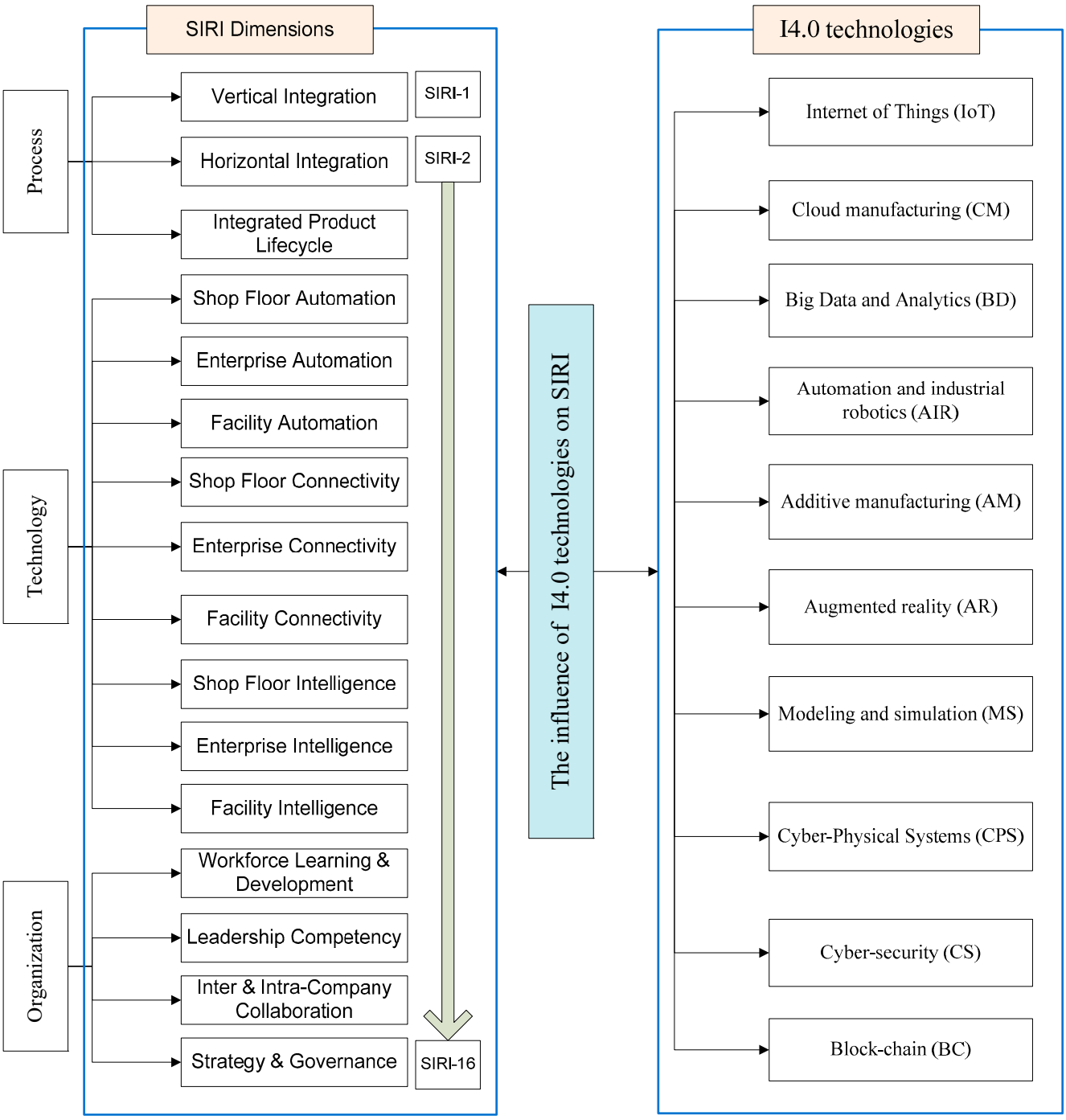


Figure 1. The influence of I4.0 Technologies on the SIRI model.

Experts who could not physically participate in person were interviewed online to explain the research. Participants received an initial email explaining the purpose of the article and confirming their involvement. The email received positive responses from most experts. Nevertheless, only eleven professionals answered the questionnaires. The selected academic specialists, therefore, have a significant influence on this field.

It must be emphasized, nevertheless, that this research depends on professional judgment in a very specialized field, the relationship between SIRI and Industry 4.0 technologies. Quality and breadth of experience were given precedence over quantity in the hiring strategy. Experts were required to have more than ten years of experience in academia or industry directly related to Industry 4.0 strategy and implementation to meet the selection criteria.

2.1. Proposed Model

To achieve competitiveness in the market, an MCDM method for I4.0 technology ranking will be created. The following steps can be used to achieve it.

2.2. Constricting the MCDM Model

The evaluation model phases intended to analyze the impact of I4.0 technologies on SIRI evaluation networks are represented in Figure 2. Researchers reviewed the relevant literature and recorded their findings in the first phase, which focused on the I4.0 concept, related technologies, and the Smart Industry Readiness Index. Interview subject-matter experts and review previous research on I4.0 technologies and rankings. With the consent of the experts, a preliminary network is created. After deciding on the evaluation's parameters, build a network framework.

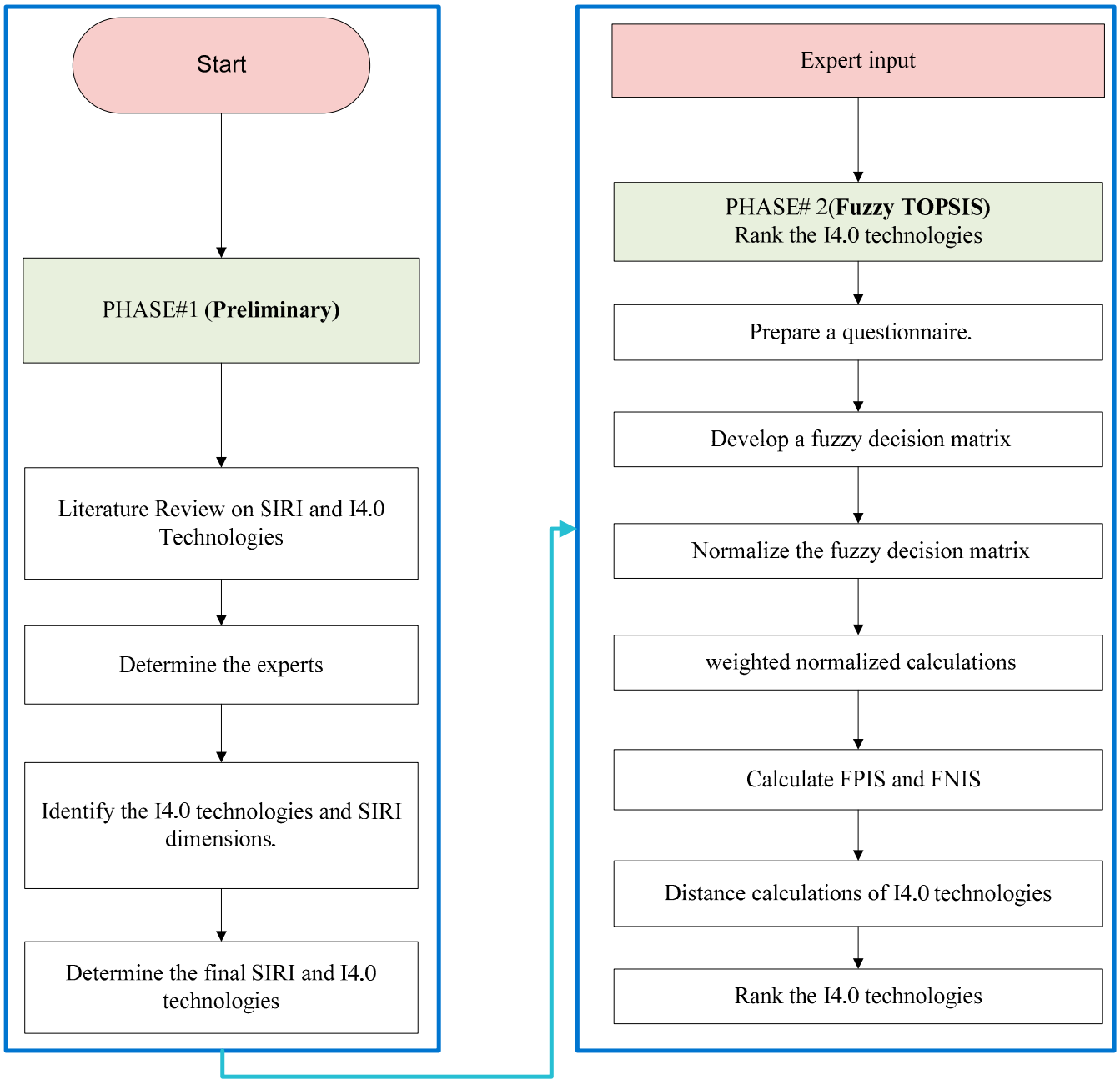


Figure 2. A fuzzy MCDM evaluation model.

2.3. Fuzzy TOPSIS Method

The fuzzy TOPSIS method for MCDM problem-solving in the presence of uncertainty is presented in this section. Decision-makers D_r(r = 1, …, k) estimate the weights of criteria and the ratings of alternatives using linguistic variables. Thus, $W_r{}^j$ represents the importance of the j^{th} criterion, C_j (j = 1, …, m), outlined by the r^{th} decision maker. Similarly, $W_r{}^j$ represents the score of the i^{th} I4.0 technology (alternatives), A_i (i = 1, …, n), Regarding criterion j, as indicated by the r^{th} decider. The fuzzy triangular numbers that Fuzzy TOPSIS requires are shown in Table 2. The following are included in the procedure under these presumptions [50–53]:

Table 2. Fuzzy TOPSIS uses linguistic variables to rate the alternatives.

Scale	The Extent of the Influence	Fuzzy Triangular Number		
VH	Very high influence	7.00	9.00	9.00
H	High influence	5.00	7.00	9.00
M	Medium influence	3.00	5.00	7.00
L	Low influence	1.00	3.00	5.00
VL	Very Low influence	1.00	1.00	3.00

Step 1. Summarize the relative importance and assessments of the options offered by k decision-makers, as indicated by Equations (1) and (2).

$$W_j = \frac{1}{k}\left[W_j^1 + W_j^2 + \ldots + W_j^k\right] \tag{1}$$

$$x_j = \frac{1}{k}\left[x_j^1 + x_j^2 + \ldots + x_j^k\right] \tag{2}$$

Step 2. The fuzzy decision matrix of criteria (W) and alternatives is combined using Equations (3) and (4).

$$D = \begin{bmatrix} \cdot & \cdot & \cdots & \cdot \\ x_{11} & x_{12} & \cdots & x_{1m} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \tag{3}$$

$$W_j = [W_1 + W_2 + \ldots + W_m] \tag{4}$$

Step 3. The options' fuzzy choice matrix (D) should be normalized using a linear-scale transformation. With Equations (5)–(7), the normalized fuzzy decision matrix R is produced.

$$R = [r_{ij}]_{m\ X\ n} \tag{5}$$

$$r_{ij} = \left(\frac{l_{ij}}{u_j^+}, \frac{m_{ij}}{u_j^+}, \frac{u_{ij}}{u_j^+}\right) \text{and } u_j^+ = max_i u_{ij}(\text{benefitcriteria}) \tag{6}$$

$$r_{ij} = \left(\frac{l_j^-}{u_{ij}}, \frac{l_j^-}{m_{ij}}, \frac{l_j^-}{l_{ij}}\right) \text{and } l_j^- = max_i l_{ij}(\text{costcriteria}) \tag{7}$$

Step 4. The weighted normalized decision matrix, V, is calculated through the multiplication of the evaluation criterion weights, W_j, by the elements of the normalized fuzzy decision matrix, r_{ij},, as shown in the following Equation (8):

$$V = [v_{ij}]_{m \times n} \tag{8}$$

where v_{ij} is given by Equation (9):

$$v_{ij} = x_{ij} \times w_{ij} \tag{9}$$

Step 5. Determine the fuzzy positive ideal solution (FPIS, A^+) and fuzzy negative ideal solution (FNIS, A^-) using Equations (10) and (11):

$$A^+ = \left\{ v_1^+, v_j^+, \ldots, v_m^+ \right\} \tag{10}$$

$$A^- = \left\{ v_1^-, v_j^-, \ldots, v_m^- \right\} \tag{11}$$

Step 6. Calculate the distances ${d_j}^+$ and ${d_j}^-$ for each alternative based on Equations (12) and (13):

$${d_j}^+ = \sum_{j=1}^{n} d_v\left(v_{ij}, v_j^+\right) \tag{12}$$

$${d_j}^- = \sum_{j=1}^{n} d_v\left(v_{ij}, v_j^-\right) \tag{13}$$

where according to the vertex, d is the separation between two fuzzy values. Equation (14) for the Corresponding Triangular Fuzzy Number (TFN) provides evidence for this.

$$d(x,z) = \sqrt{\frac{1}{3}\left[(l_x - l_z)^2 + (m - m_z)^2 + (u_x - u_z)^2\right]} \tag{14}$$

Step 7. Applying Equation (15), determine the closeness coefficient CC_i:

$$CC_i = \frac{{d_j}^+}{{d_j}^+ + {d_j}^-} \tag{15}$$

Step 8. The best option is the one that is closest to the FPIS and furthest from the FNIS. Use the closeness coefficient, CC_i, to determine the decreasing order of the options.

3. Results and Discussion

This section describes how the TOPSIS ranking method is applied to I4.0 technologies. Furthermore, the elements that most significantly influence the overall differentiation of each technology can be identified, enabling the creation and application of practical improvements in manufacturing organizations. For each SIRI, the experts use a questionnaire to determine what the customer expects from each I4.0 Technology. The questionnaire is given to eleven experts, k1–k11, and ten technologies are analyzed. Due to space constraints in this article, Table 3 provides only an example of the data gathered from one expert for the evaluation of the alternative. Tables 4 and 5 display the distance from fuzzy positive and negative ideal solutions, respectively. Consequently, the distances ${d_j}^+$ and ${d_j}^-$ for each choice and the closeness coefficient CC_i I4.0 technologies are displayed in Table 6. Table 6 displays the final ranking of I4.0 technologies along with the closeness coefficients.

To calculate these values, Equation (15) was used. Based on the data, CPS received a score of 0.7218, placing it as the first Technology Influence SIRI. Often, computer and physical processes are integrated into cyber-physical systems, which communicate with each other through feedback loops. They play a growing role in various engineering fields, facilitating developments in areas such as smart manufacturing, smart grids, and autonomous vehicles. Physical processes, frequently involving sensors, actuators, and communication networks, are integrated with computational elements through CPS.

Table 3. One expert provided a sample of the data gathered to evaluate alternatives.

I4.0	SIRI-1	SIRI-2	SIRI-3	SIRI-4	SIRI-5	SIRI-6	SIRI-7	SIRI-8	SIRI-9	SIRI-10	SIRI-11	SIRI-12	SIRI-13	SIRI-14	SIRI-15	SIRI-16
IoT	VH	H	H	VH	H	VH	VH	VH	VH	VH	H	H	M	M	H	H
CM	H	VH	H	M	VH	H	H	VH	H	M	VH	H	H	H	VH	VH
BD	H	H	VH	M	H	M	H	H	H	VH	VH	VH	H	VH	H	VH
AIR	H	M	H	VH	H	VH	H	M	H	H	M	H	H	M	M	H
AM	M	H	VH	H	M	H	M	M	M	H	H	M	VH	H	H	H
AR	M	L	H	H	M	H	M	M	M	H	M	H	VH	H	H	M
MS	H	H	VH	H	H	H	M	H	M	VH	VH	H	H	H	H	H
CPS	VH	VH	VH	VH	H	VH	VH	VH	VH	VH	VH	VH	H	H	H	VH
CS	H	H	M	H	VH	H	VH	VH	VH	H	VH	H	VH	VH	H	VH
BC	M	VH	H	L	M	L	M	H	M	L	H	L	H	H	VH	H

Table 4. Distance from fuzzy positive ideal solution (FPIS).

I4.0	SIRI-1	SIRI-2	SIRI-3	SIRI-4	SIRI-5	SIRI-6	SIRI-7	SIRI-8	SIRI-9	SIRI-10	SIRI-11	SIRI-12	SIRI-13	SIRI-14	SIRI-15	SIRI-16	d_j^+
IoT	0.000	0.385	0.035	0.047	0.012	0.093	0.000	0.058	0.146	0.070	0.130	0.141	0.035	0.082	0.035	0.152	1.421
CM	0.292	0.261	0.082	0.181	0.035	0.093	0.093	0.082	0.152	0.140	0.146	0.159	0.070	0.105	0.035	0.173	2.100
BD	0.304	0.166	0.128	0.208	0.105	0.128	0.070	0.082	0.173	0.082	0.159	0.166	0.082	0.093	0.070	0.152	2.167
AIR	0.282	0.266	0.093	0.133	0.012	0.000	0.058	0.140	0.173	0.117	0.181	0.190	0.070	0.187	0.093	0.141	2.136
AM	0.282	0.152	0.105	0.199	0.105	0.082	0.047	0.082	0.047	0.023	0.023	0.093	0.012	0.117	0.093	0.000	1.461
AR	0.332	0.423	0.082	0.173	0.152	0.128	0.181	0.199	0.173	0.082	0.181	0.146	0.058	0.152	0.082	0.159	2.702
MS	0.311	0.217	0.175	0.208	0.128	0.140	0.208	0.070	0.217	0.140	0.181	0.173	0.035	0.152	0.093	0.173	2.621
CPS	0.261	0.257	0.000	0.000	0.023	0.105	0.000	0.035	0.128	0.000	0.000	0.000	0.012	0.058	0.000	0.137	1.015
CS	0.266	0.137	0.058	0.166	0.000	0.047	0.023	0.000	0.133	0.035	0.129	0.159	0.000	0.000	0.035	0.137	1.324
BC	0.317	0.082	0.187	0.226	0.140	0.266	0.190	0.140	0.181	0.140	0.173	0.269	0.082	0.128	0.117	0.152	2.790

Table 5. Distance from fuzzy negative ideal solution (FNIS).

I4.0	SIRI-1	SIRI-2	SIRI-3	SIRI-4	SIRI-5	SIRI-6	SIRI-7	SIRI-8	SIRI-9	SIRI-10	SIRI-11	SIRI-12	SIRI-13	SIRI-14	SIRI-15	SIRI-16	d_j^-
IoT	0.332	0.163	0.152	0.190	0.140	0.190	0.208	0.159	0.105	0.070	0.105	0.190	0.047	0.105	0.082	0.035	2.271
CM	0.070	0.181	0.105	0.058	0.117	0.190	0.146	0.146	0.093	0.000	0.058	0.166	0.012	0.082	0.082	0.000	1.506
BD	0.047	0.266	0.058	0.023	0.047	0.166	0.159	0.146	0.058	0.058	0.035	0.159	0.000	0.093	0.047	0.035	1.397
AIR	0.093	0.166	0.093	0.152	0.140	0.266	0.166	0.129	0.058	0.023	0.000	0.141	0.012	0.000	0.023	0.058	1.521
AM	0.093	0.273	0.082	0.035	0.047	0.199	0.173	0.146	0.181	0.117	0.166	0.210	0.070	0.070	0.023	0.173	2.058
AR	0.000	0.000	0.105	0.070	0.000	0.166	0.035	0.000	0.058	0.058	0.000	0.181	0.023	0.035	0.035	0.023	0.790
MS	0.035	0.257	0.012	0.023	0.023	0.159	0.000	0.152	0.000	0.000	0.000	0.152	0.047	0.035	0.023	0.000	0.918
CPS	0.163	0.217	0.187	0.226	0.128	0.181	0.208	0.173	0.175	0.140	0.181	0.269	0.070	0.128	0.117	0.070	2.634
CS	0.140	0.287	0.128	0.082	0.152	0.226	0.190	0.199	0.140	0.105	0.117	0.166	0.082	0.187	0.082	0.070	2.351
BC	0.023	0.396	0.000	0.000	0.012	0.000	0.023	0.129	0.047	0.000	0.012	0.000	0.000	0.058	0.000	0.035	0.735

Table 6. Fuzzy TOPSIS result (distances and closeness coefficient).

I4.0 T.	Distance from FPIS (d_i^+)	Distance from FNIS (d_i^-)	Closeness Coefficients (CC_i)	Rank
IoT	1.421	2.271	0.6150	3
CM	2.100	1.506	0.4177	5
BD	2.167	1.397	0.3919	7
AIR	2.136	1.521	0.4158	6
AM	1.461	2.058	0.5849	4
AR	2.702	0.790	0.2263	9
MS	2.621	0.918	0.2593	8
CPS	1.015	2.634	0.7218	1
CS	1.324	2.351	0.6398	2
BC	2.790	0.735	0.2085	10

Consequently, cyber-physical systems offer several benefits, including safety and effectiveness, as well as the ability to enable collaboration between different entities to create complex systems with new capabilities. Cyber-physical technology can be used in many different fields, such as manufacturing, agriculture, social networking and gaming, medical devices and integrated systems, telemedicine, alternative energy, environmental control, telepresence, safe and efficient transportation, critical infrastructure control, assisted living, and social networking and gaming [54]. The Smart Industry Readiness Index (SIRI) places a high value on cyber-physical systems because they enable the seamless integration of digital and physical processes, facilitating intelligent decision-making, agile production, and real-time automation in smart manufacturing environments. By implementing them, facilities become more competitive, efficient, and adaptable in the Industry 4.0 era by fostering greater maturity in SIRI's core dimensions, including connectivity, automation, and vertical integration.

Cybersecurity is listed as the second technology. The growing dependence on digital technologies and interconnected systems makes factories susceptible to cyberattacks that can compromise safety, disrupt operations, and steal data, which is why computer science is essential to smart manufacturing. The quick development of digital technologies and the growing complexity of cyberthreats have shaped the dynamic and ever-changing cybersecurity landscape in smart manufacturing (especially in the supply chain) [55]. The increasing volumes and dependence on data present a significant challenge for CS, making cybersecurity essential to the advancement of smart manufacturing and corporate competitiveness. Data assets will increasingly serve as a gauge of a company's market value, making this particularly crucial. Human and machine safety will become increasingly crucial as automation and system autonomy continue to increase [56].

The foundational layer of trust and security for an interconnected industrial environment is cybersecurity, which makes it an essential part of the Smart Industry Readiness Index. From worker devices to supply chain systems and automated machinery, every element of a smart factory is digitally connected. While increasing efficiency and productivity, this interconnectedness also gives cybercriminals a large attack surface. To protect vital data, prevent business interruptions, and safeguard intellectual property, robust cybersecurity measures are essential. Production halts, financial loss, and serious reputational harm are just a few of the disastrous outcomes that could result from a single breach in the absence of a robust cybersecurity framework. Thus, in the SIRI framework, cybersecurity is not only an IT issue but also a key facilitator of industrial transformation.

According to the list, the third technology that impacted SIRI was the Internet of Things (IoT). Through the Internet of Things, physical objects can exchange information, coordinate actions, and communicate with one another [32]. The term "Industrial Internet

of things" (IIoT), which emphasizes the industrial applications of the Internet of Things, is frequently used in the context of Industry 4.0 [57]. The Internet of Things is widely utilized in various industries, including construction, healthcare, and transportation [58]. One of the most critical enablers in the SIRI framework is IoT. It offers the essential data collection and connectivity features that support a smart factory. The Internet of Things enables real-time data transfer from the physical world to digital systems by integrating sensors and actuators into equipment, goods, and buildings. Numerous advantages are made possible by this constant flow of information, including supply chain transparency, optimized production processes, and predictive maintenance. Since IoT is the key technology that enables the gathering and sharing of operational data, the other SIRI pillars— automation, connectivity, and intelligence—cannot operate efficiently without it. Among I4.0 technologies, additive manufacturing (AM) is ranked fourth. Cloud manufacturing is ranked as the fifth I4.0 technology (CM). In the context of implementing I4.0 technologies, other technologies are generally of moderate or lower relevance to SIRI, as indicated in Table 6.

The Ranking of I4 Technologies According to Each SIRI

The ranking of I4.0 technologies provides a detailed and strategic guide for businesses, based on each of the three SIRI dimensions (Technology, Process, and Organization). A more nuanced understanding of which technologies have the most significant influence on a particular area of industrial readiness replaces a single, general "best" list. In a multi-criteria decision-making approach, experts evaluate technologies like IoT and CM against the sub-pillars of each dimension, such as assessing their influence on Shop Floor Automation (under the Technology dimension), Vertical Integration (under the Process dimension), and Leadership Competency (under the Organization dimension). By doing this, a company can create a detailed, pillar-specific prioritization that directly aligns its technology investments with its most pressing strategic goals. The ranking's outcomes are shown in Figure 3. For every SIRI consolidated finding, it displays the differentiation indices and the relative relationships. The ranking of other I4 technologies by SIRI is depicted in Figure 3. It shows that, among all the I4.0 technologies regarding vertical integration, IoT has the highest overall score of 0.811. Following this are CS and BC.

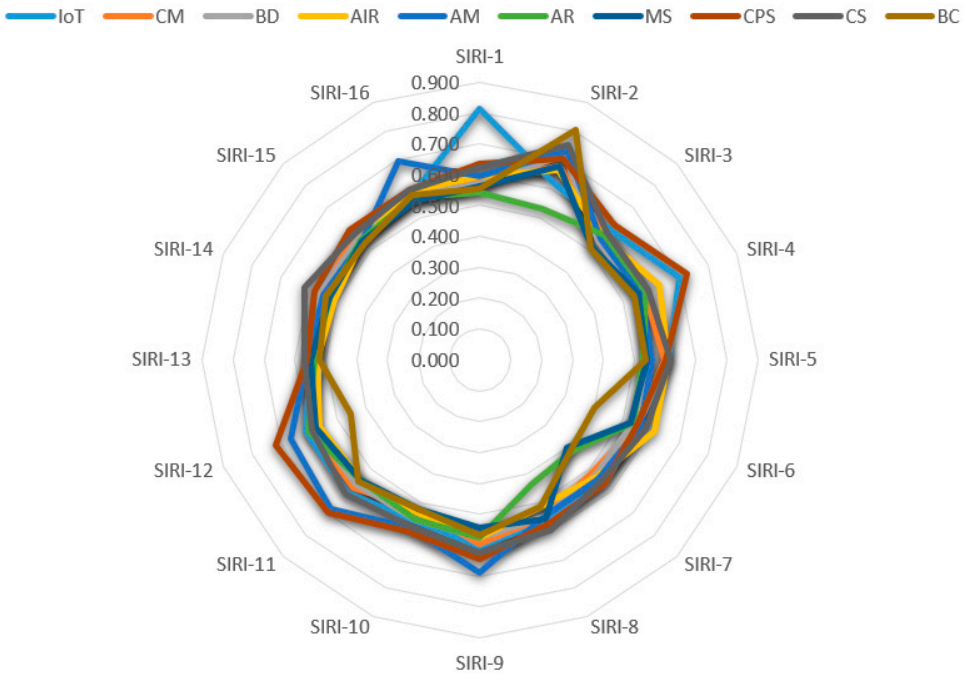


Figure 3. The ranking of I4 technologies according to SIRI.

4. Sensitivity Analysis

Sensitivity analysis is used to show how different criterion weights affect I4.0 technology rankings. This was done to show how changing the weights would affect the final TOPSIS results and other rankings. The purpose of the sensitivity analysis in this article is to examine the consistency and robustness of the ranking according to the weight of the criteria. Furthermore, it focuses on enhancing this model's output both qualitatively and quantitatively, taking into account the sensitivity of decision-making that arises from ambiguous input values. The primary purpose of this research is to analyze the Smart Industry Readiness Index (Process, Technology, and Organization).

Table 7 illustrates how the weights of the decision criteria were altered for each of the four scenarios. Following that, the closeness coefficients (*CC i*) were ascertained using the TOPSIS technique. The sensitivity analysis results are displayed in Table 8. It should be noted that the model's output is shown in the first row of the table (Scenario 1). The sensitivity analysis is represented graphically in Figure 4. The ranking of the model is not significantly impacted by altering the criteria weights, as shown in Table 8. Under all evaluated scenarios, however, the Cyber-Physical system (CPS) obtained the highest *CC i* value. Consequently, the Smart Industry Readiness Index selected CPS as the best I4.0 technology.

Table 7. The configuration of sensitivity analysis.

	Process	Technology	Organization
Scenario#1	Every weight is the same: 1/n can complete this one, where n is the number of dimensions.		
Scenario#2	33.33% of the total weight is assigned for process dimensions (33.33/3)	33.33% of the total weight is assigned for Technology dimensions (33.33/9)	33.33% of the total weight is assigned for Organization dimensions (33.33/9)
Scenario#3	20%	50%	30%
Scenario#4	25%	40%	35%

Table 8. Results of the sensitivity analysis.

I4.0 tech.	Scenario#1		Scenario#2		Scenario#3		Scenario#4	
	Closeness Coefficients	Rank	Closeness Coefficients	Rank	Closeness Coefficients	Rank	Closeness Coefficients	Rank
IoT	0.6150	3	0.5962	3	0.6075	3	0.5976	3
CM	0.4177	5	0.3879	5	0.4097	5	0.3961	5
BD	0.3919	7	0.3792	6	0.3871	7	0.3806	6
AIR	0.4158	6	0.3676	7	0.4000	6	0.3764	7
AM	0.5849	4	0.5455	4	0.5792	4	0.5636	4
AR	0.2263	9	0.1887	10	0.2197	9	0.2042	10
MS	0.2593	8	0.2648	9	0.2579	8	0.2590	8
CPS	0.7218	1	0.6485	1	0.7076	1	0.6768	1
CS	0.6398	2	0.6187	2	0.6387	2	0.6313	2
BC	0.2085	10	0.2699	8	0.2168	10	0.2409	9



Figure 4. Sensitivity analysis.

5. Implications

In recent years, Industry 4.0 technologies have garnered considerable attention from researchers. Nevertheless, there is currently no systematic method to help a company assess and select the best I4.0 technologies. Therefore, the purpose of this article is to use a fuzzy MCDM to rank the different I4.0 technologies related to SIRI. The goal of the article was to create a more effective method for ranking and choosing I4.0 technologies. The managerial implications of implementing Industry 4.0 technology to enhance SIRI within businesses are the primary focus of this section.

Cluster managers, researchers, practitioners, and decision-makers can all benefit from the useful information this model offers. A crucial contribution is determining how I4.0 technologies affect SIRI. As smart manufacturing techniques gain traction, businesses focus on the features of manufacturing systems that are impacted by technological advancements. To develop smart manufacturing systems, I4.0 technologies are the key enablers needed. However, the selection and extent of these technologies may vary according to the organization's strategic choices regarding the desired level of intelligence. An organization's readiness to adopt smart manufacturing for a specific process, manufacturing asset, and facility is indicated by its degree of smartness. I4.0 technologies must be in line with long-term strategic objectives in order to improve manufacturing performance in every category.

Based on the valuable management implications of I4.0 technologies, this article also provides managers with essential insights for enhancing their adoption. According to the article's findings, managers must give the appropriate I4.0 technologies top priority for production planning in order to become competitive in the market and get relevant feedback. Organizations can optimize the advantages of integrating these technologies into well-established and well-designed processes thanks to the ranking. Additionally, by demonstrating the importance of these technologies in providing a business with a competitive edge, this research supports the shift from traditional to smart manufacturing.

Using the Smart Industry Readiness Index to rank Industry 4.0 technologies provides organizations with a clear framework for evaluating their digital maturity and benchmarking against industry standards, enabling them to identify their strengths, weaknesses, and top areas for improvement. This methodical ranking enhances decision-making, supports effective resource allocation, aligns transformation plans with business objectives, and results in targeted investment in the most impactful technologies. Ultimately, SIRI provides

businesses with the tools they need to overcome the challenges of digital transformation, thereby enhancing competitiveness, productivity, and innovation.

A key element of the Smart Industry Readiness Index (SIRI) is Cyber-Physical Systems (CPS), which allow manufacturers to seamlessly integrate the digital and physical worlds, fostering the intelligence, agility, and efficiency necessary for Industry 4.0 adoption. CPS are essential to the SIRI because they provide the technological foundation for highly automated, networked production environments. Manufacturers can utilize real-time data and sophisticated analytics to monitor, control, and optimize physical processes, thanks to the facilitation of sensor integration, control systems, and networking infrastructure. This connectivity enhances operational responsiveness and transparency, enabling businesses to quickly adapt to changing production needs and market demands. Through data collection and analysis, CPS provides intelligence that aids manufacturers in decision-making, downtime reduction, and product quality improvement. To evaluate technological maturity, the SIRI framework requires these specific capabilities.

6. Conclusions

This article aims to analyze the influence of I4.0 technologies on SIRI. It uses a fuzzy MCDM model to rank the I4.0 technologies. Both theoretically and practically, this research makes a substantial contribution. By identifying I4.0 technologies, SIRI advances knowledge of the Smart Industry Readiness Index and the Fourth Industrial Revolution. This research has provided theoretical insights for further empirical research on the relationship between SIRI and Industry 4.0. The study's conclusions specifically recommend that manufacturing companies select appropriate I4.0 technologies in order to compete on a worldwide scale. It provides a particular perspective on ranking I4.0 technologies among SIRI. Organizations can better appreciate the advantages of incorporating these technologies into well-thought-out and established processes thanks to this ranking. By using the right technology, performance was enhanced, and competitiveness was attained. Additionally, by demonstrating how these technologies can be crucial in giving businesses a competitive edge, this research helps organizations make the shift from traditional to smart manufacturing.

The results revealed that the Cyber-Physical System (CPS) is the most suitable I4.0 technology for countering global competition, followed by CS and IoT. Other I4.0 technologies are moderately or less relevant to SIRI when I4 technologies are used.

To gain a better understanding of the issue's full scope, future research and development may integrate various methods, such as BWM or PROMETHEE, and conduct further surveys with a larger sample size to generalize the results. As the adoption of I4.0 technologies is still in its infancy in most industries, no case article or empirical article has been conducted to determine the effects of I4.0 technologies on SIRI. Additionally, investigate how well the SIRI framework works for small and medium-sized businesses, identifying any necessary modifications or customized interventions to improve Industry 4.0 adoption in SMEs.

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