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Strategic Roadmap for Prioritizing Industry 4.0 Technologies in Manufacturing: Integrating DFSS and MCDA Approaches

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Abstract

Industry 4.0, also known as the Fourth Industrial Revolution, has completely changed the manufacturing landscape by utilizing technology 4.0 to increase productivity, efficiency, and flexibility. Setting priorities for technology is crucial to achieving the best possible implementation as manufacturing companies transition to Industry 4.0. This abstract provides a framework that combines the Design for Six Sigma (DFSS) approach with multi-criteria decision-making (MCDM) methods to assess the readiness of manufacturing firms for Industry 4.0 adoption. At the core of the DFSS approach, we specifically utilized MCDA in the analysis phase, focusing on the key considerations and challenges. A comprehensive assessment of technologies, including artificial intelligence (AI), the Internet of Things (IoT), cyber-physical systems (CPS), augmented reality (AR), and big data, is part of the prioritizing process. Investment expenses, system integration complexity, security, and return on investment are key evaluation criteria. We also used Factory IO software in the last phase of the DFSS approach to verify, test, validate, and optimize process designs prior to real implementation. Experts can prioritize technologies that support their strategic objectives by using this approach. This study contributes a structured pathway for manufacturing industries to navigate the complexities of digital transformation with an emphasis on expert precision and quality improvement.

Keywords: Industry 4.0; Decision-making Methods; Technologies 4.0; Design for Six Sigma; Smart Manufacturing; Factory IO.

1. Introduction

Industry 4.0 is often described as a novel phase in industry evolution, characterized by the convergence of various emerging technologies to provide digital solutions. Nevertheless, there remains a gap in comprehension regarding how companies actually integrate these technologies into their operations [1]. The integration of cutting-edge technology into the industrial sector, such as artificial intelligence (AI), the Internet of Things (IoT), data analytics, and robots, is what sets Industry 4.0 apart. This technological transition is projected to transform how things are developed, manufactured, and distributed, resulting in increased efficiency, productivity, and personalization. Industry 4.0 includes the digitization of every link in the value chain, from the raw material to the finished product to the customers, to improve responsiveness, clarity, and cooperation. In essence, it signifies a substantial transformation for manufacturing companies [2]. Industry 4.0 (I4.0) technologies capture the spirit of this digital revolution, changing traditional appliances into smart devices that may incorporate contemporary technology, therefore having a significant impact on the industrial sector [3]. Manninen and Hujkonen [4] Recognizing that the successful implementation of technological innovations within an organization is influenced by a range of environmental, organizational, and technical factors, it becomes crucial to grasp the implications of these technologies to harness their added value. This underscores the significant benefits the manufacturing industry has reaped from the adoption of Industry 4.0 technologies [5]. It is beneficial to explore the Industrial Revolution because it has contributed significantly to economic development. Traditional production sectors drive today's digital and artificial intelligence (AI) production systems, which are fueled by exponentially increasing technology. To highlight the significance of competitiveness and economic growth, It is imperative that nations and their industrial systems keep up with or adjust to rapid advances in technology. Throughout history, various types of technological inventions have influenced a country's economic growth or fall. Because new technologies allow each worker to produce more products and services, technological development initiatives improve labor productivity and advance economic growth. [6]. The industry's evolutionary stages, from 1.0 to 4.0, are depicted in Figure 1.

- First Industrial Revolution: Industry 1.0 is the term used to characterize the first industrial revolution,

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began during the end of the 18th century and resulted in the establishment of the first factories that manufactured mechanical goods. Technological advancements (such as water frame, spinning Jenny, weaving machines, and the steam engine) defined this revolution [7].

- Second Industrial Revolution: Spanned the years from the turn of the 20th century to the 1970s, during which mass production methods powered by electricity and the division of labor were introduced, along with the first production and assembly lines. Fuelled by technological advancements like electricity and petroleum [8].
- Third Industrial Revolution: signifies a substantial change toward technology that is information-centric, as several research studies have noted. This revolution, which began in the 1970s, focuses on the combination of physical manufacturing and digital information processing, resulting in decentralized and customized production techniques [9].
- Fourth Industrial Revolution: was coined during Hannover Fair in 2011 by a group of German corporates, academic, and government professionals in the course of a presentation on a project concerning German manufacturing. This project aims to boost the German industrial sector's competitiveness by investing in innovative digital technologies and solutions [10].

In two years, the same group would produce the well-known "Final Report of the Industry 4.0 Working Group" [11], which explains the idea of Industry 4.0 as well as a vision and recommendations for the future of the German manufacturing industry.

Manufacturing industries must prepare for the application of 4.0 technologies, This necessitates that they comprehend every element and facet of Industry 4.0. Aside from understanding its capabilities, they must also recognize its implementation difficulties and comprehend how these difficulties affect 4.0 technologies, as well as which ones will have the greatest impact. This article focuses on evaluating and prioritizing 4.0 technologies before their implementation in manufacturing industries.

2. Methodological framework:

In assessing the pre-implementation stage of Industry 4.0 technologies in manufacturing, the integration of Design for Six Sigma (DFSS) with a multi criteria decision analysis (MCDA) approach Like (Fuzzy AHP OR Fuzzy TOPSIS) can provide a structured and quantitative strategy to evaluate and prioritize technology investments. These techniques might be used to provide a complete pre-implementation evaluation tool for Industry 4.0 technology in the manufacturing sector.

- **Define Phase:** Identify the Industry 4.0 technologies and the obstacles that stand in the way of their implementation.
- **Measure Phase:** Establish baseline metrics to evaluate each Industry 4.0 technology under consideration (e.g., cost, compatibility, network security).
- **Analyze Phase:** Use Fuzzy TOPSIS OR Fuzzy AHP within the DFSS framework to rank potential technologies based on these metrics
- **Design Phase:** Design a tailored solution roadmap for each technology based on its ranking and assessment.
- **Verify Phase:** Conduct a pilot test for top-ranked technologies, verifying that they meet the success factors, allowing adjustments before full-scale implementation.

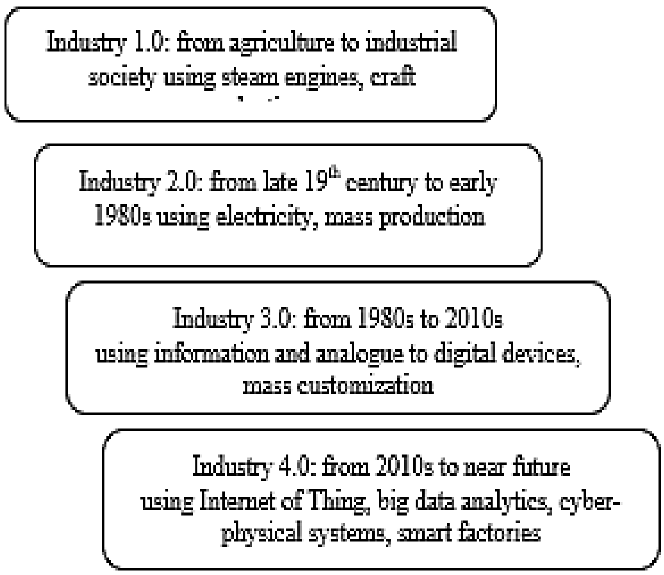

Figure 1. Evolution of industry 4.0. Source: Adapted from [8].

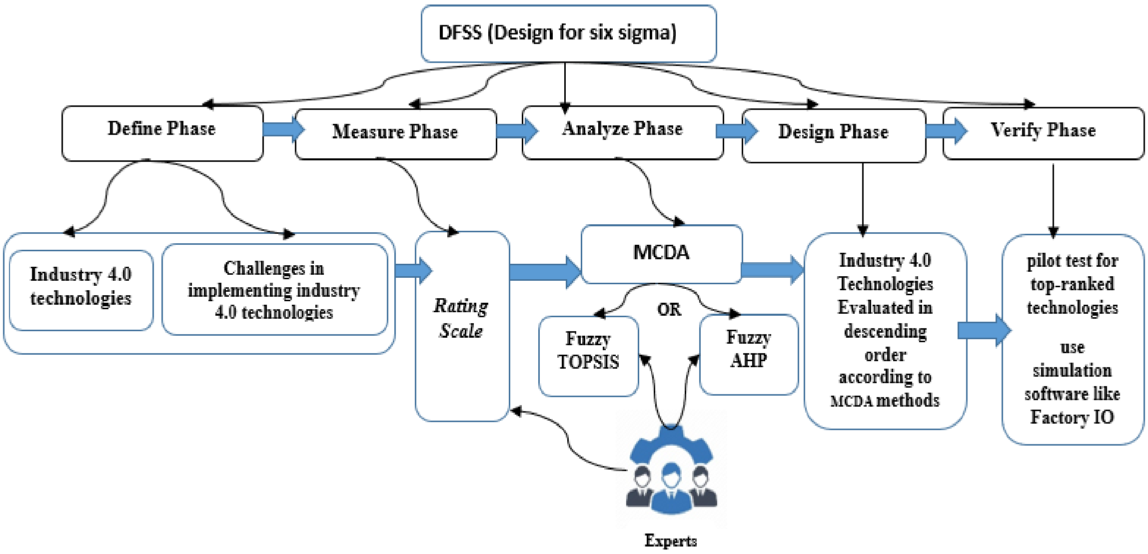

Figure 2. Integration of Design for Six Sigma (DFSS) with a multi criteria decision analysis (MCDA) approach for assessing the pre-implementation stage of industry 4.0 technology.

3. Define Phase:

3.1. Key technologies integrated into Industry 4.0:

In this section, we reference significant technologies that encompass a broad spectrum of software and equipment. When integrated, these technologies have the potential to elevate a manufacturing company into an intelligent one [12].

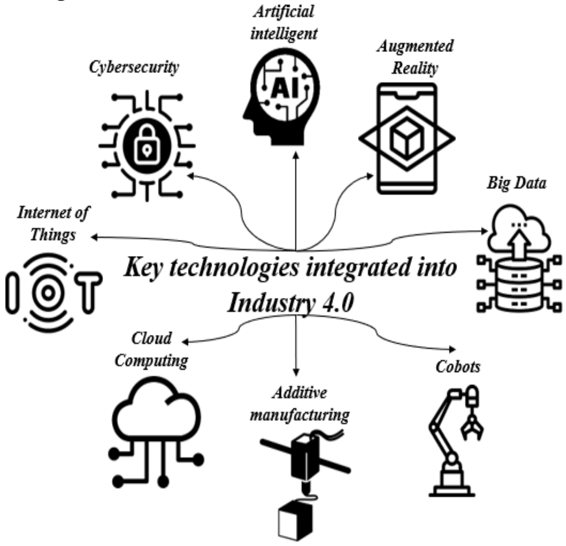

Figure 3.Key Technologies integrated into Industry 4.0.

- **Cybersecurity:**

Fredrick Chang [13], the former Director of Research of the National Security Agency in the United States, emphasizes the interdisciplinary aspect of cybersecurity: "*A science of cybersecurity offers many opportunities for advances based on a multidisciplinary approach, because, after all, cybersecurity is fundamentally about an adversarial engagement. Humans must defend machines that are attacked by other humans using machines. So, in addition to the critical traditional fields of computer science, electrical engineering, and mathematics, perspectives from other fields are needed*."

- **Additive manufacturing:**

Additive manufacturing (AM) is a rapid manufacturing technique that moves from point to line, body, and surface. AM is powered by discrete data and takes full use of both real-time intelligent control technologies and mechanical properties performance regulation during printing. Parts are printed from the bottom up, utilizing layer-by-layer deposition [14].

- **Augmented Reality:**

Augmented reality (AR) is closely associated with the concept of virtual reality (VR). While VR aims to construct an artificial environment for users to engage with primarily through their senses of vision, as well as tactile, audio, and other feedback, AR provides an interactive experience designed to enhance the real world rather than fabricate a wholly fictional one. In AR, tangible elements within the user's environment serve as the backdrop and targets for computer-generated annotations [15].

- **Cloud Computing:**

Cloud computing is a technology that allows reliable data storage and management, offering opportunities to capitalize on the potential of Cyber-Physical Systems and the Internet of Things [16]. Industry 4.0 relies heavily on cloud computing since it allows real-time data integration and exchange between business lines [17]. Through the use of data science, machine learning, and artificial intelligence, it facilitates IoT on a wide scale and at a low cost, making it easier to integrate industrial operational technology with information technology [18]. Industry 4.0 is centered around cloud technology, which uses robots, intelligent sensors, and artificial intelligence to drive creative and effective business process methods [19].

- **Big Data:**

Gartner, Inc [20] defines big data: "*Big data is high-volume, high-velocity and high-variety information assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision making*." Similarly, The TechAmerica Foundation [21] defines big data as follows:"*Big data is a term that describes large volumes of high velocity, complex and variable data that* *require advanced techniques and technologies to enable the capture, storage, distribution, management, and analysis of the information.*"

- **Internet of Things:**

One way to describe the Internet of Things (IoT) is as the result of the Internet's radical evolution coupled with a network of networked items that form an intelligent environment. IoT is a system of digitally connected devices with individual identities having the capacity to transmit information without involving human-to-human or human-to-computer communication. [22].

- **Cobots:**

A cobot, is designed to work alongside people in a shared workplace, carrying out activities that call for both robotic and human abilities. Actuality, cobots are considered an asset to human labor, leveraging their special qualities such as adaptability and analytical skills [23]. Owing to continuous automation and digital transformation sparked by Industry 4.0, cobot presence in companies has expanded. This has led to significant changes in employment characteristics, such as responsibilities, work environment, teamwork, and work structure. Thus, integrating new technology into an organization may have the effect of altering the socio-organizational structure [24].

- **Artificial intelligent:**

One of the cornerstones of Industry 4.0 is Artificial Intelligence (AI). For example, it enables process, quality control, and predictive maintenance optimization. All facets of smart manufacturing, including production tracking and machine state monitoring, leverage AI by utilizing IoTs to gather data. Additionally, fleet management and robot route optimization are made possible by artificial intelligence in smart manufacturing. Artificial Intelligence has applicability across the entire production and management systems of a company [25].

3.2. Challenges in Implementing Industry 4.0 Technologies

It is crucial to recognize and evaluate the challenges that industrial companies face while implementing Industry 4.0. In our analysis, we pinpoint seven challenges to the adoption of Industry 4.0.

In this research, we used Scopus as the primary database. Scopus examines a vast array of material to provide dependable, source-neutral statistics and metrics that provide meaningful insights on institutions, authors, and research domains. Scopus data serves as a reliable resource for guiding research planning and decision-making for universities, ranking organizations and funding agencies [6]. The search was performed on August 8, 2024, using the following string: TITLE-ABS-"Challenges AND (in AND (Implementing AND (Industry AND (4.0 AND Technologies))))". This search strategy effectively discovered 529 articles that fulfilled the specified criteria. The findings include conference papers and journal articles without any limitation on the time period. The first publication in the collection was published in 2015, so offering coverage spanning 10 years (2015-2024). Every article underwent meticulous and rigorous scrutiny to eliminate any biases in the analysis. As a result, unpublished publications, ongoing research articles, and conference proceedings only included a table of contents were omitted from the study. The aim of this process was to guarantee that the chosen papers concentrated only on the challenges associated with the implementation of Industry 4.0 technology. Following this refinement, 22 publications were eliminated, resulting in a final dataset of 507 papers kept for the analysis of the conceptual framework of the analyzed research. A bibliometric study was conducted. The research used the visualization of similarities (VOS) technique, using all keywords as the analytical unit. This facilitated a thorough comprehension of the linkages and patterns among the keywords.

3.2.1. Keyword Co-Occurrence Analysis

To execute the primary analysis. VOSviewer version 1.6.9 was used for co-word analysis. This software made it easier to examine and visualize word linkages and co-occurrence patterns. Using keywords, the approach develops a knowledge framework that allows for the identification of the principal subjects and their links within a field of study. Figure 04 depicts the cluster map Viewer keywords set from

the Scopus database. The network is mapped using only words with high recurrence counts; hence, the threshold was set at 2, and 694 keywords still present. Total keywords show a cluster map with 16 clusters. In this analysis, we extracted the terms related to the challenges in implementing industry 4.0 technology from the 694-keywords presented by VOS. Table 1 resumes these challenges with its apparencies.

Table 1. Challenges extracted from Vos

Challenges keywords	Appearance	Total link strength
agile measures	2	11
agility	3	31
costs	8	72
change management	3	17
data integration	4	39
data privacy	6	54
education	9	50
education computing	5	39
electronic data interchange	7	66
engineering education	24	192
environmental impact	4	33
environmental sustainability	5	53
flexible systems	2	16
flexibility	3	30
higher education	3	23
higher education institutions	3	18
implementation process	7	61
implementation projects	3	21
information management	17	148
integration	8	71
investments	5	53
interoperability	11	91
knowledge management	3	13
learning systems	8	105
network security	10	90
risk assessment	4	23
safety	3	31
security	3	32
security of data	6	58
security systems	3	32
sustainability	35	234
sustainable development	40	339
technology implementation	4	22
workforce	3	29

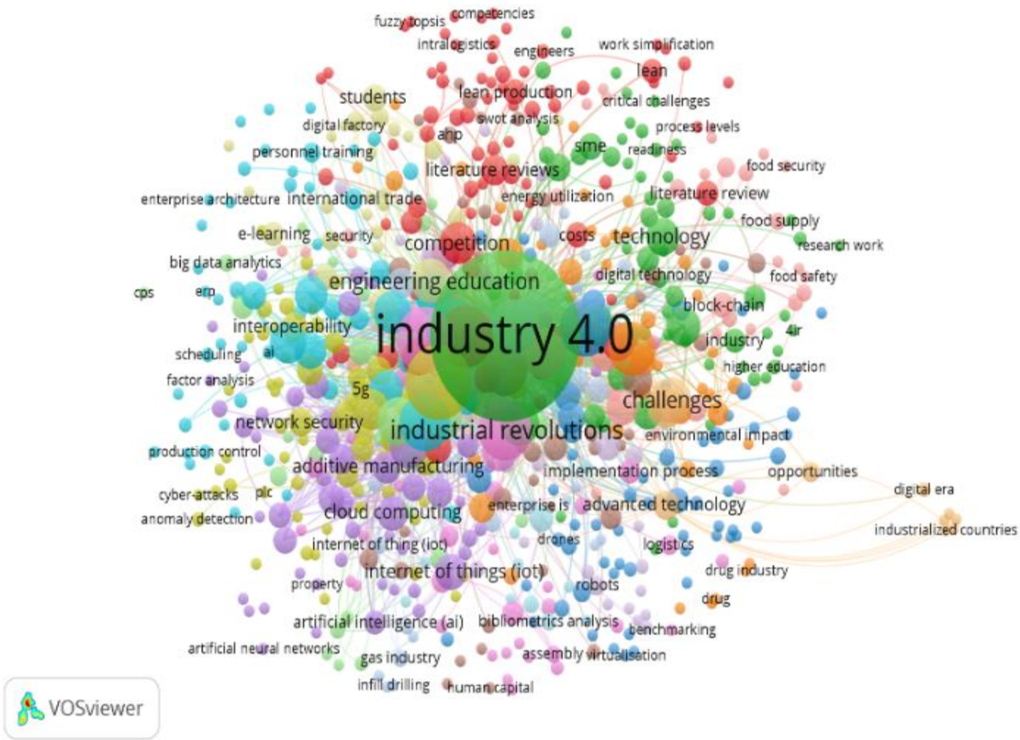

Figure 4. Keyword co-occurrence analysed by Vos software

Certain keywords possess identical meanings and implications, necessitating their amalgamation into a one term. The keywords "Engineering education," "Learning system," and "higher education" are distinct yet synonymous, collectively addressing the challenge of workforce. Similarly, the keywords "implementation process," "data integration," "integration," and "interoperability" represent the challenge of interoperability and integration. Thus, we amalgamate analogous keywords to elucidate specific challenges. Table 2 delineate the main challenges in Implementing Industry 4.0 Technologies, along with their prevalence, as determined by our bibliometric study.

Table 2.The main challenges in implementing industry 4.0 technologies

Challenges	Appearance
Environmental and sustainability	84
workforce	58
Interoperability and Integration	37
Data security	35
change management	27
cost	13
Flexibility and Agility	10

- **Cost:**

The costs associated with Industry 4.0 technology and process integration in the manufacturing sector are a key problem in commencing the company's transformation process [26]. Large capital investments are necessary to drive innovation based on sophisticated technology and system processes. Capital allocation, budgeting, and financial planning are critical [27]. Direct and indirect expenses could also be included; Direct expenses may arise from the introduction of modern technology, the initial purchase of hardware or software, and employee education. While operating expenses associated with system transformations, short-term productivity losses, and other related expenses brought on by modifications to corporate systems and procedures can all be considered indirect costs. [28].

- **Change management:**

The implementation of Industry 4.0 technologies presents significant challenges in change management, primarily due to the complexity of digital transformation and the need for organizational adaptation. Approximately 70% of change initiatives fail due to poor management support and unclear objectives [29]. Employees often perceive new technologies as threats to their job security, leading to reluctance in embracing change [30]. Insufficient understanding of new technologies, such as AI and automation, contributes to anxiety and resistance among staff [31].

- **Interoperability and Integration:**

Every organization has different standards, procedures, interfaces, special features, and technologies that make integration more difficult [32]. The integration of Industry 4.0 technologies in industrial companies presents a multifaceted challenge due to the complexity involved in adopting these advanced systems. Research indicates that Industry 4.0 encompasses technologies like IoT, cobots, AI, and CPS, revolutionizing industrial processes.[33]

- **Workforce Absorption:**

The human workforce is one of the main implementation challenges of Industry 4.0, as automation gradually replaces existing jobs and roles in the manufacturing sector, people will continue to organize this industrial revolution. Nonetheless, most workers face challenges such a lack of industry-specific knowledge, which lowers staff productivity. Employers are now able to accept Industry 4.0 more readily because the application of state-of-the-art Cyber-Physical Systems in Industry 4.0-based work organization strategies has stimulated innovation and raised intrinsic motivation [34].

- **Flexibility and Agility:**

Flexibility is defined as the capacity to formulate and choose options for a specific situation. Regarding manufacturing, "ability of a manufacturing system to develop and select alternatives for a particular manufacturing situation is known as MF" [35]. In the Industry 4.0 age, agility has a specific significance [36]. Agility is said to give companies the capacity and guidance they require to effectively configure their Industry 4.0 technology [37].

- **Data Security:**

Industry 4.0's rapidly increasing amount of heterogeneous data and the trend toward information migration to cloud systems increase security risk awareness. The ability to remotely control physical objects raises the risk associated with industrial data compared to a typical data system. The increasing trend of integrating IT into production processes is making our lives simpler. However, from a security sense, this might possibly be a "time bomb" [38].

- **Environmental and sustainability:**

The implementation of Industry 4.0 (I4.0) technologies presents significant environmental and sustainability challenges, despite their potential benefits. While these technologies can enhance efficiency and reduce waste, their integration often encounters obstacles that hinder achieving strong sustainability goals.

For example, In the textile sector, while I4.0 technologies promote micro-level circular economy practices, they often neglect broader sustainability actions, indicating a gap in achieving strong sustainability [39]. Meeting stringent environmental regulations is a challenge, as industries must adapt their practices to comply with standards like ISO 14001[40].

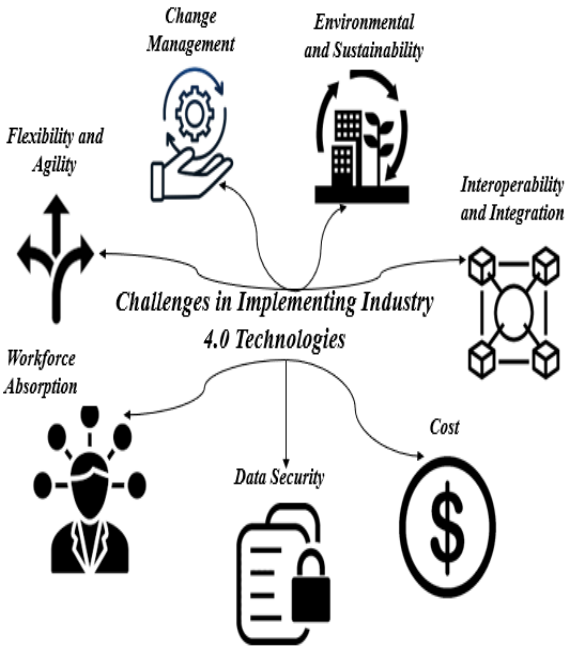

Figure 5.Challenges in implementing industry 4.0 technologies

4. Measure Phase:

The objective of the study presented in this paper is to prioritize Industry 4.0 technologies in the manufacturing industry before the implementation process, taking into account specific challenges and considerations. So, we will use in the next phase 2 multicriteria decision methods (fuzzy TOPSIS and Fuzzy AHP), the industry 4.0 technology represent the alternative and the challenges represent the criteria, we will use fuzzy scale to evaluate alternatives and criterions for the both methods.

5. Analyze Phase

In this phase we use Fuzzy-TOPSIS and Fuzzy AHP prioritize these Industry 4.0 technologies. The criteria represent the challenges of Industry 4.0 technologies before implementation, and the alternatives represent the various Industry 4.0 technologies. We discuss the deference between the two methods and which one is the best for a case study continent 8 alternative and 7 criteria.

5.1. Fuzzy TOPSIS

- **Fuzzy TOPSIS theory details:**

Lai, and Liu [41] optimized TOPSIS, which was initially created by Hwang and Yoon in 1981[42]. It is an effective method for dealing multi-attribute or multi-criteria decision-making (MADM/MCDM) difficulties in the actual world. It assist decision maker(s) (DMs in organizing the issues to be addressed, as well as doing the appropriate analysis, comparisons, and ranking of the alternatives. The chosen alternative must have the lowest geometric distance from the positive ideal solution (PIS), and the largest geometric distance from the negative ideal solution (NIS), according to the main tenet of TOPSIS [43].

It is a compensatory aggregation technique that establishes weights for every criterion in order to compare a group of alternatives.

In multi-criteria problems, evaluation challenges can arise due to misalignment in the dimensions of parameters or criteria. To address these challenges, the use of a Fuzzy system becomes essential. Fuzzy system or sets are mathematical means of representing vagueness and precise information, Accordingly the term used is fuzzy [44]. The theory of this logic is based on fuzzy set. This logic imitates human thinking and natural language which makes it different from traditional logical system [45]. Incorporating Fuzzy numbers into TOPSIS for criteria analysis offers a straightforward and practical modeling approach, in addition to a compensation plan that permits the addition or removal of alternative solutions based on hard cut-offs [46].

5.1.1. Fundamental definitions:

- **Fuzzy set definition**

The fuzzy set A¯ in X is defined by:

$$\tilde{A} = \{x, \mu_{\boldsymbol{A}}(x)\}, x \in X \qquad (1)$$

Where $\mu_{\boldsymbol{A}}(x) : X \rightarrow [0, 1]$ is the membership function of $\tilde{A}$ and $\mu_{\boldsymbol{A}}(x)$is the degree of relevance of x in $\tilde{A}$, x does not belong to the fuzzy set $\tilde{A}$ if $\mu_{\boldsymbol{A}}(x) = 0$. If $\mu_{\boldsymbol{A}}(x) = 1$, then x is totally within the fuzzy set $\tilde{A}$. In contrast to the classical set theory, x partially belongs to the fuzzy set A˜ if μ_A(x) has a value between zero and one. This means that the relevance of x is true with degree of membership given by $\mu_{A}(x)$ [47].

- **Fuzzy numbers definition**

A fuzzy set whose membership function meets the normality conditions is called a fuzzy number.

$$\sup \tilde{A}\,(X)_{x \in X} = 1 \quad (2)$$

And of convexity

$$\widetilde{D}=\begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{11} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} \quad (3)$$

For all x1, x1 ∈ X and all λ ∈ [0,1]. The triangular fuzzy number is frequently utilized in decision making because of its obvious membership function, $\tilde{w}=[\tilde{w}_1+\tilde{w}_2+\ldots+\tilde{w}_m]$ given by:

$$\mu_{A}(x) = \begin{cases} 0 & for\ x < 1 \\ \frac{x-l}{m-l} & for\ l \le x \le u \\ \frac{u-x}{u-m} & for\ m \le x \le u \\ 0 & for\ x > u \end{cases} \quad (4)$$

Where l < m < u and l, m, and u are real numbers.

The highest pertinence degree is indicated by m, whereas outside of the interval [l, u], The pertinence degree is zero. Additionally, in decision-making processes, trapezoidal fuzzy numbers are often utilized. [48].

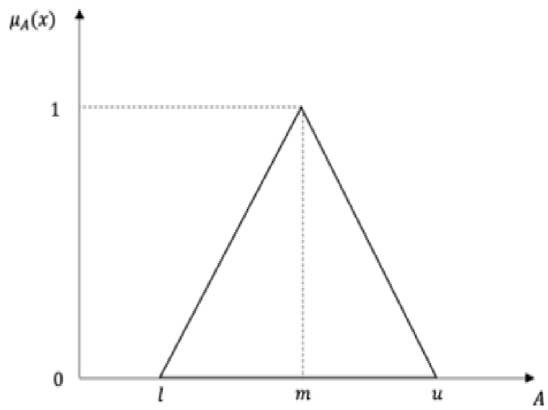

Figure 6. Triangular Fuzzy number (TFN)

5.1.2. Fuzzy TOPSIS steps:

Step 01: Aggregate the ratings of alternatives and weights of criteria provided by k decision makers, as shown in equations (5) and (6), respectively:

$$\tilde{w}_J=\frac{1}{k}\,[\tilde{w}_j^1+\tilde{w}_j^2+\ldots+\tilde{w}_j^k] \quad (5)$$

$$\tilde{x}_{ij}=\frac{1}{k}\,[\tilde{x}_{ij}^1+\tilde{x}_{ij}^2+\ldots+\tilde{x}_{ij}^k] \quad (6)$$

Step 02: Constructing the fuzzy decision matrix of the criteria (w˜) and the alternatives (D˜) with equations (7) and (8):

$$\widetilde{D}=\begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{11} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} \quad (7)$$

$$\tilde{w}=[\tilde{w}_1+\tilde{w}_2+\ldots+\tilde{w}_m] \quad (8)$$

Step 03: Use linear scale transformation to normalize the alternatives' fuzzy decision matrix (D˜). The normalized fuzzy decision matrix $\widetilde{R}$ is defined as:

$$\widetilde{R}=[\tilde{r}_{ij}]_{m\times n} \quad (9)$$

$$\tilde{r}_{ij}=\left(\frac{l_{ij}}{u_j^+},\frac{m_{ij}}{u_j^+},\frac{u_{ij}}{u_j^+}\right) \text{ and } u_j^+=\max_i u_{ij} \text{ (Benefit criteria)} \quad (10)$$

$$\tilde{r}_{ij}=\left(\frac{l_j^-}{u_{ij}},\frac{l_j^-}{m_{ij}},\frac{l_j^-}{l_{ij}}\right) \text{ and } l_j^-=\min_i l_{ij} \text{ (cost criteria)} \quad (11)$$

Step 04: The components r˜ij of the normalized fuzzy decision matrix are multiplied by the weights of the evaluation criteria, w˜j, to create the weighted normalized decision matrix, V˜.

$$\widetilde{V}=[\tilde{v}_{ij}]_{m\times n} \quad (12)$$

where v˜ij is given by Eq. (13).

$$\tilde{v}_{ij}=\tilde{x}_{ij}\times\tilde{w}_j \quad (13)$$

Step 05: Define the Fuzzy Positive Ideal Solution (FPIS, A+) and the Fuzzy Negative Ideal Solution (FNIS, A−), according to equations. (14) and (15).

$$A^+=\{\tilde{v}_1^+,\tilde{v}_j^+,\ldots\ldots,\tilde{v}_m^+\} \quad (14)$$

$$A^-=\{\tilde{v}_1^-,\tilde{v}_j^-,\ldots\ldots,\tilde{v}_m^-\} \quad (15)$$

Where $\tilde{v}_1^+=(1,1,1)$ and $\tilde{v}_1^-=(0,0,0)$

Step 06: Determine each alternative's d+ j and d− i distances from v˜ + j and v˜ − j, respectively, using the provided equations (16) and (17):

$$d_i^+=\sum_{j=1}^{n} d_v(\tilde{v}_{ij},\tilde{v}_j^+) \quad (16)$$

$$d_i^-=\sum_{j=1}^{n} d_v(\tilde{v}_{ij},\tilde{v}_j^-) \quad (17)$$

The distance between two fuzzy numbers using the vertex method is represented by d(.,.). Regarding triangular fuzzy numbers, this is stated as in equation. (18).

$$d(\tilde{x},\tilde{z})=\sqrt{\frac{1}{3}[(l_x-l_z)^2+(m_x-m_z)^2+(u_x-u_z)^2]} \quad (18)$$

Step 07: Calculate the closeness coefficient, CCi, using equation. (19).

$$cc_i=\frac{d_i^-}{d_i^++d_i^-} \quad (19)$$

Step 08: Use the closeness coefficient, or CCi, to rank the alternatives. The best alternatives are located closest to the FPIS and furthest away from the FNIS.

- **Case study:**

This study aims to prioritize technologies 4.0 Before implementation in manufacturing industries. The study was carried out in N'gaous-Conserves Industry, which is located in N'gaous, Batna[1] Province. This company still relies on industry 3.0 technologies such as automation in mass (industrial robots, PLC, and CNC), and the digitalization process (CAO, FAO, PLM, MES, ERP,

[1]Batna Province is situated in northeastern Algeria, ranking as the fifth largest city in the country.

CRM, etc...). To make the shift to Industry 4.0 easier, the company faced many challenges, including financial challenges, compatibility, integration complexity, workforce absorption, flexibility and agility, data security, and environmental and sustainability. That's why it needed to evaluate and prioritize technologies 4.0 by looking at their challenges before the implementation.

Seven challenges toward Industry 4.0 implementation in industrial sectors are identified. and represented by criteria; eight technologies were defined and represented by alternatives (Table 3), comprising the most widely discussed technologies within the realm of Industry 4.0. Figure 07 illustrates the hierarchical structure of the proposed model.

The next step is establishing a contextual link between the challenges and technology. 4.0.

Three experts were chosen to assess the established criteria, and they were provided with comprehensive information about the issue. who has sufficient ability to analyze and evaluate the technologies that are compatible with the company.

Using linguistic terms, the decision-makers evaluated the weight of the criterion as well as the ratings of the alternatives. The linguistic values of these variables are expressed using triangular fuzzy numbers (TFN), as Tables 4 and 5 demonstrate.

Table 3.Representation of criteria and alternatives

Criteria name	Representative	Alternatives name	Representative
Cost	CR1	Internet of Things	A1
Change Management	CR2	Cobots	A2
Interoperability and Integration	CR3	Artificial intelligence	A3
Workforce Absorption	CR4	Big Data	A4
Flexibility and Agility	CR5	Augmented Reality	A5
Data Security	CR6	Additive Manufacture	A6
Environmental and sustainability	CR7	Cyber Security	A7

Table 4.Linguistic expressions used for evaluation of alternatives [46].

Fuzzy numbers	**Linguistic term**
(1,1,3)	Very low (VL)
(1,3,5)	Low (L)
(3,5,7)	Medium (M)
(5,7,9)	High (H)
(7,9,9)	Very High (VH)

Table 5.fuzzy scale used for evaluation of criterion [49].

Fuzzy number	QA Weights
(1,1,1)	Important (I)
(2,3,4)	Moderately important (MI)
(4,5,6)	Strongly important (SI)
(6,7,8)	Very strong important (VSI)
(8,9,9)	Extreme important (EI)

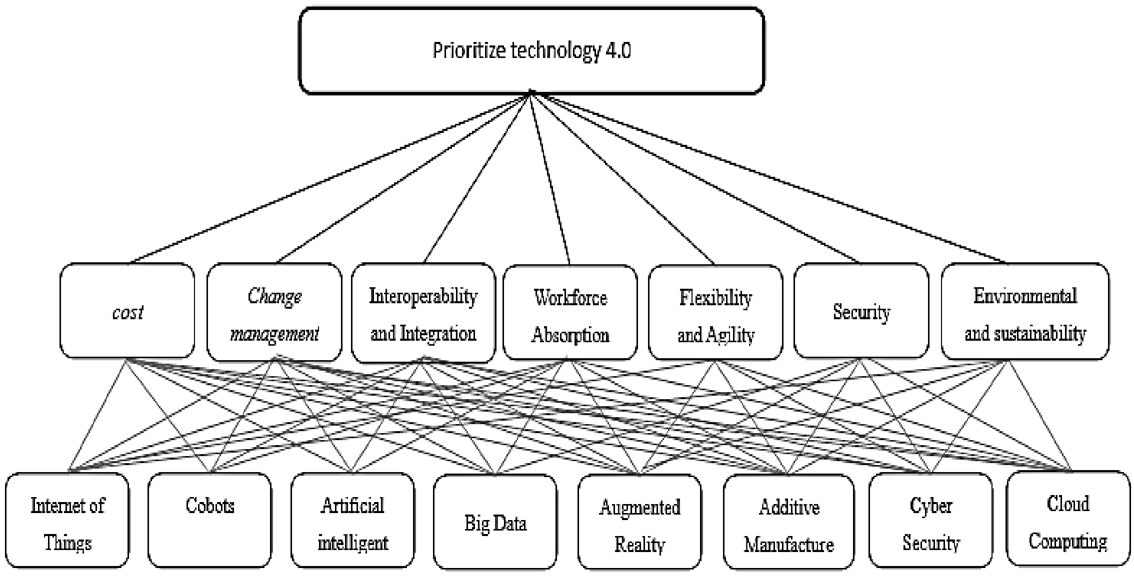

Figure 7. Hierarchical structure of proposed model.

Table 6. Decision makers' linguistic evaluations of the alternatives.

Criteria Alternative	CR1	CR2	CR3	CR4	CR5	CR6	CR7
DM1							
Weights of criteria	SI	VSI	SI	MI	MI	EI	SI
A1	M	H	L	L	H	M	H
A2	VH	M	H	M	H	H	VH
A3	H	H	H	L	VH	H	VH
A4	M	H	L	L	L	H	M
A5	M	M	M	M	H	M	M
A6	M	M	L	M	H	M	H
A7	H	H	M	L	H	VH	H
A8	VH	H	M	M	H	VH	H
DM2							
Weights of criteria	SI	EI	SI	SI	MI	VSI	VSI
A1	H	H	M	M	H	H	H
A2	H	M	H	H	H	M	VH
A3	H	VH	H	L	VH	VH	H
A4	H	H	M	L	M	H	H
A5	M	H	L	M	VH	M	M
A6	M	M	L	H	H	L	M
A7	H	H	H	L	VH	VH	H
A8	H	VH	M	L	H	VH	VH
DM3							
Weights of criteria	VSI	VSI	VSI	MI	MI	VSI	EI
A1	H	H	M	H	H	H	VH
A2	VH	H	M	M	M	M	VH
A3	H	H	VH	L	H	H	VH
A4	H	M	M	M	H	M	H
A5	H	M	M	M	M	M	M
A6	H	M	VL	H	M	L	M
A7	VH	H	M	L	H	VH	H
A8	VH	H	M	L	H	H	VH

We display the parameters of the TFN derived from aggregating of decision makers depicted in (linguistic evaluations of the alternatives).

After that we displayed the normalized fuzzy decision matrix and the weighted normalized fuzzy decision matrix, respectively. The fuzzy negative ideal solution (FNIS, A-) and fuzzy positive ideal solution (FPIS, A+) are defined as follows by Chen [50]:

A+ = [(1, 1, 1), (1, 1, 1), (1, 1, 1), (1, 1, 1), (1, 1, 1), (1, 1, 1), (1, 1, 1)]

A− = [(0, 0, 0), (0, 0, 0), (0, 0, 0), (0, 0, 0), (0, 0, 0) (0, 0, 0), (0, 0, 0)]

we displayed the distances di + representing the ratings of each alternative from A+, obtained using equation (16). Finaly, we obtained the distances di- of each alternative's ratings from A- using equation (17).

In this case study, Decision Maker prioritizes IoT as the most significant technologies (Table 7 and Figure 08). IoT and AI are crucial technologies for this company that wants to implement technology 4.0

Table 7. Outranking of technologies 4.0 according to our case study

Alternatives	d+	d-	cci	Rank
A1	6,05	9,06	0,600	1
A2	8,16	6,68	0,45	5
A3	6,05	8,87	0,59	2
A4	8,59	6,37	0,426	6
A5	9,47	5,31	0,36	8
A6	8,55	6,23	0,422	7
A7	6,52	8,50	0,57	4
A8	6,23	8,70	0,58	3

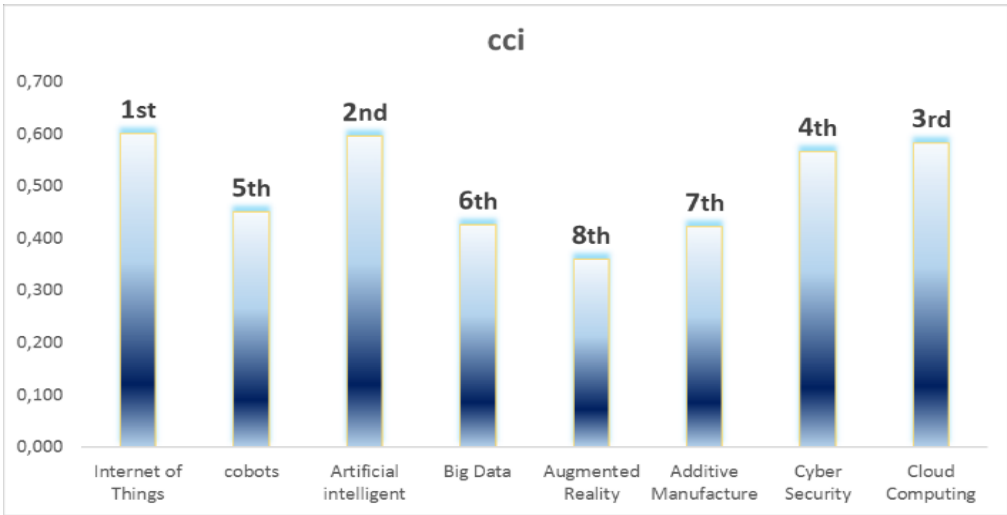

Figure 8.Outranking of technologies 4.0 for this case study.

5.2. Fuzzy AHP

AHP aids in capturing both subjective and objective assessment measures of the available alternative options, hence minimising decision-making bias [51]. AHP is achieved by creating pairwise comparison matrices based on expert judgements. The comparisons are based on scaling absolute judgements, which offers a measure of how significant one choice is in contrast to others based on a certain criterion [52].

Chang [53] proposed extent analysis-based FAHP. The technique uses linguistic variables to describe decision makers' comparative judgments. Let X = {x1. xi. . . .. xn} represent an object set and T= {t1. tj. . . .. tm} a target set. In the method proposed by Chang [54]. each object, xi, is taken and extent analysis is performed for each target. Tj. Thus. m extent analysis values for each object can be obtained. with the following signs:

$$M_{ti}^{1}. M_{ti}^{j}. \dots . M_{ti}^{m}. \quad i=1.2\dots\dots n \tag{20}$$

where all the M_{ti}^{j} (j = 1. 2. . . .. m) are triangular fuzzy numbers. The method follows the steps described next.

Step 01: Compute the value of the fuzzy synthetic extent with respect to the ith object according to Eq. (21).

$$s_i = \sum_{j=1}^{m} M_{ti}^{i} * \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{ti}^{i}\right]^{-1} \tag{21}$$

Where $\sum_{j=1}^{m} M_{ti}^{i}$ obtained by performing the fuzzy additionoperation of m extent analysis values for a particular matrix such that

$$\sum_{j=1}^{m} M_{ti}^{i} = \left(\sum_{j=1}^{m} lj . \sum_{j=1}^{m} mj . \sum_{j=1}^{m} uj\right) \tag{22}$$

And $\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{ti}^{i}\right]^{-1}$ is given by

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{ti}^{i}\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{m} u_i} . \frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{m} m_i} . \frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{m} l_i}\right) \tag{23}$$

Step 02: Compute the degree of possibility of $s_2(l_2. m_2. u_2) \geq s_1 = s_2(l_1. m_1. u_1)$. where S2 and S1are given by Eq. (21). The degree of possibility between two fuzzy synthetic extents is defined as in Eq. (24)

$$V(s_2 \geq s_1) = sup_{y \geq x} = [\min(\mu_{s2}(y).\ \mu_{s1}(x))] \tag{24}$$

which can be equivalently expressed as in Eqs. (25) and (26).

$$V(s_2 \geq s_1) = \text{hgt}(s_1 \cap s_2) = \mu_{s2}(d) \tag{25}$$

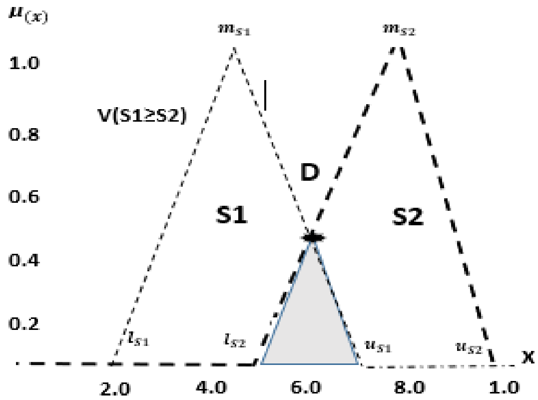

Figure 9. The intersection between S1and S2.

$$\mu_{s2} \begin{cases} 1. & if\ m_1 \geq m_2 \\ 0. & if\ l_1 \geq u_2 \\ \frac{l_1 - u_2}{(m_2-u_2)-(m_1-l_1)} & Otherwise \end{cases} \tag{26}$$

In equations (25) and (26). d is the ordinate of the apex intersection point D between μ_s1 and μ_s2, as illustrated in Figure 9. The comparison of M1 and M2 necessitates the values of V ($s_2 \geq s_1$) and V ($s_1 \geq s_2$) .

Step 03: Calculate the likelihood that a convex fuzzy number exceeds k convex fuzzy numbers S_i (i = 1. . . .. k). This is determined in accordance with Equation (27).

$$V = S \geq S_1. S_2 \dots . S_k$$
$$= V\,[(S \geq S_1) \text{ and } (S \geq S_2) \text{ and } \dots\dots (S \geq S_k)] \tag{27}$$
$$= \min V\,(S \geq S_i)\ .\ i=1.2.\dots.k$$

Step 04 : Compute the vector w'. which is given by Eq. (28).

$$w' = (d'(A_1).\ d'(A_2).\ \dots .\ d'(A_k))^T \tag{28}$$

assuming that

$$d'(A_1) = \min V\ (s_i \geq s_j).\ \text{for } i=1.\ 2.\ldots.k\ .\ j=1.2.\ldots.k.\quad k \neq j \tag{29}$$

The normalized vector is indicated by

$$W = (d(A_1).\ d'(A_2).\ \ldots .\ d(A_k))^T \tag{30}$$

where the value of W is a number that is not fuzzy and is calculated for each comparison matrix

- **Fuzzy AHP application**

To compare the weight of the criteria and the evaluations of the alternatives, the experts employed the language phrases shown in Fig. 10. Following Chang [53]. To define these variables' linguistic values, TFN was utilised. according to Table 8.

The three experts' comparative assessments of the weights of the criteria that were previously translated into TFN are shown in Table 9

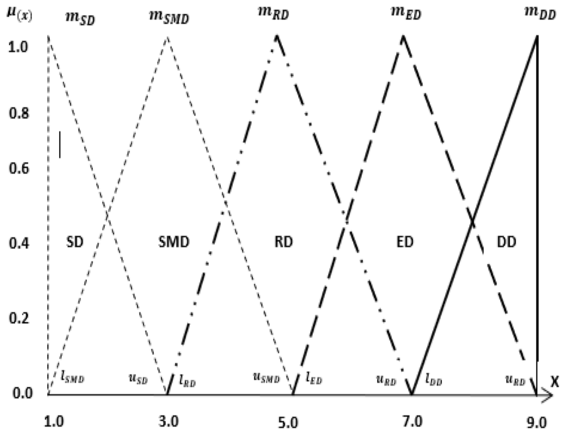

Figure 10. Linguistic comparison of criteria weights and alternatives ratings.

Table 8. Alternatives grading and criteria weighting comparative linguistic scale.

Linguistic terms Fuzzy	triangular number
Similarly desirable. (SD)	(1.0. 1.0. 3.0)
Slightly more desirable. (SMD)	(1.0. 3.0. 5.0)
rather desirable. (RD)	(3.0. 5.0. 7.0)
Extremely desirable. (ED)	(5.0. 7.0. 9.0)
Definitely desirable. (DD)	(7.0. 9.0. 9.0)

Table 9. Comparing Experts' criteria weights

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**
D1							
C1	(1.0. 1.0. 1.0)	(0.2. 0.3. 1.0)	(0.2. 0.3. 1.0)	(0.2. 0.3. 1.0)	(0.3. 1.0. 1.0)	(0.2. 0.3. 1.0)	(0.2. 0.3. 1.0)
C2	(1.0. 3.0. 5.0)	(1.0. 1.0. 1.0)	(0.3. 1.0. 1.0)	(0.2. 0.3. 1.0)	(0.2. 0.3. 1.0)	(0.1. 0.2. 0.3)	(1.0. 1.0. 3.0)
C3	(1.0. 3.0. 5.0)	(1.0. 1.0. 3.0)	(1.0. 1.0. 1.0)	(0.2. 0.3. 1.0)	(0.3. 1.0. 1.0)	(0.2. 0.3. 1.0)	(0.3. 1.0. 1.0)
C4	(1.0. 3.0. 5.0)	(1.0. 3.0. 5.0)	(1.0. 3.0. 5.0)	(1.0. 1.0. 1.0)	(1.0. 3.0. 5.0)	(0.3. 1.0. 1.0)	(0.3. 1.0. 1.0)
C5	(1.0. 1.0. 3.0)	(1.0. 3.0. 5.0)	(1.0. 1.0. 3.0)	(0.2. 0.3. 1.0)	(1.0. 1.0. 1.0)	(0.2. 0.3. 1.0)	(0.2. 0.3. 1.0)
C6	(1.0. 3.0. 5.0)	(3.0. 5.0. 7.0)	(1.0. 3.0. 5.0)	(1.0. 1.0. 3.0)	(1.0. 3.0. 5.0)	(1.0. 1.0. 1.0)	(0.1. 0.2. 0.3)
C7	(1.0. 3.0. 5.0)	(0.3. 1.0. 1.0)	(1.0. 1.0. 3.0)	(1.0. 1.0. 3.0)	(1.0. 3.0. 5.0)	(3.0. 5.0. 7.0)	(1.0. 1.0. 1.0)
D2							
C1	(1.0. 1.0. 1.0)	(0.1. 0.2. 0.3)	(0.1. 0.2. 0.3)	(0.1. 0.1. 0.2)	(1.0. 3.0. 5.0)	(0.1. 0.2. 0.3)	(0.1. 0.2. 0.3)
C2	(3.0. 5.0. 7.0)	(1.0. 1.0. 1.0)	(0.2. 0.3. 1.0)	(0.2. 0.3. 1.0)	(0.3. 1.0. 1.0)	(0.2. 0.3. 1.0)	(1.0. 3.0. 5.0)
C3	(3.0. 5.0. 7.0)	(1.0. 3.0. 5.0)	(1.0. 1.0. 1.0)	(0.2. 0.3. 1.0)	(0.3. 1.0. 1.0)	(0.2. 0.3. 1.0)	(0.3. 1.0. 1.0)
C4	(5.0. 7.0. 9.0)	(1.0. 3.0. 5.0)	(1.0. 3.0. 5.0)	(1.0. 1.0. 1.0)	(0.3. 1.0. 1.0)	(0.3. 1.0. 1.0)	(0.2. 0.3. 1.0)
C5	(0.2. 0.3. 1.0)	(1.0. 1.0. 3.0)	(1.0. 1.0. 3.0)	(1.0. 1.0. 3.0)	(1.0. 1.0. 1.0)	(0.2. 0.3. 1.0)	(0.1. 0.2. 0.3)
C6	(3.0. 5.0. 7.0)	(1.0. 3.0. 5.0)	(1.0. 3.0. 5.0)	(1.0. 1.0. 3.0)	(1.0. 3.0. 5.0)	(1.0. 1.0. 1.0)	(0.1. 0.2. 0.3)
C7	(3.0. 5.0. 7.0)	(0.2. 0.3. 1.0)	(1.0. 1.0. 3.0)	(1.0. 3.0. 5.0)	(3.0. 5.0. 7.0)	(3.0. 5.0. 7.0)	(1.0. 1.0. 1.0)
D3							
C1	(1.0. 1.0. 1.0)	(0.1. 0.2. 0.3)	(0.1. 0.2. 0.3)	(0.3. 1.0. 1.0)	(0.3. 1.0. 1.0)	(0.2. 0.3. 1.0)	(0.2. 0.3. 1.0)
C2	(3.0. 5.0. 7.0)	(1.0. 1.0. 1.0)	(1.0. 1.0. 3.0)	(0.2. 0.3. 1.0)	(0.1. 0.2. 0.3)	(0.2. 0.3. 1.0)	(0.3. 1.0. 1.0)
C3	(3.0. 5.0. 7.0)	(1.0. 1.0. 3.0)	(1.0. 1.0. 1.0)	(0.2. 0.3. 1.0)	(0.3. 1.0. 1.0)	(0.1. 0.2. 0.3)	(0.2. 0.3. 1.0)
C4	(1.0. 1.0. 3.0)	(1.0. 3.0. 5.0)	(1.0. 3.0. 5.0)	(1.0. 1.0. 1.0)	(3.0. 5.0. 7.0)	(0.3. 1.0. 1.0)	(0.3. 1.0. 1.0)
C5	(1.0. 1.0. 3.0)	(3.0. 5.0. 7.0)	(1.0. 1.0. 3.0)	(0.1. 0.2. 0.3)	(1.0. 1.0. 1.0)	(0.2. 0.3. 1.0)	(0.2. 0.3. 1.0)
C6	(1.0. 3.0. 5.0)	(1.0. 3.0. 5.0)	(3.0. 5.0. 7.0)	(1.0. 1.0. 3.0)	(1.0. 3.0. 5.0)	(1.0. 1.0. 1.0)	(0.1. 0.2. 0.3)
C7	(1.0. 3.0. 5.0)	(1.0. 1.0. 3.0)	(1.0. 3.0. 5.0)	(1.0. 1.0. 3.0)	(1.0. 3.0. 5.0)	(3.0. 5.0. 7.0)	(1.0. 1.0. 1.0)

The criteria matrix fuzzy synthetic extent values are:

$S_{c1} = (2.45, 4.22, 6.73) \otimes (\frac{1}{128.28}, \frac{1}{78.51}, \frac{1}{43.60})$
$= (0.019, 0.054, 0.154)$

$S_{c2} = (5.22, 8.90, 14.55) \otimes (\frac{1}{128.28}, \frac{1}{78.51}, \frac{1}{43.60})$
$= (0.041, 0.113, 0.334)$

$S_{c3} = (5.33, 9.39, 14.78) \otimes (\frac{1}{128.28}, \frac{1}{78.51}, \frac{1}{43.60})$
$= (0.042, 0.120, 0.339)$

$S_{c4} = (7.39, 15.44, 23.00) \otimes (\frac{1}{128.28}, \frac{1}{78.51}, \frac{1}{43.60})$
$= (0.058, 0.197, 0.527)$

$S_{c5} = (5.23, 6.91, 14.55) \otimes (\frac{1}{128.28}, \frac{1}{78.51}, \frac{1}{43.60})$
$= (0.041, 0.088, 0.334)$

$S_{c6} = (8.14, 16.20, 26.33) \otimes (\frac{1}{128.28}, \frac{1}{78.51}, \frac{1}{43.60})$
$= (0.063, 0.206, 0.604)$

$S_{c7} = (9.84, 17.44, 28.33) \otimes (\frac{1}{128.28}, \frac{1}{78.51}, \frac{1}{43.60})$
$= (0.077, 0.222, 0.650)$

The degrees of possibility of these fuzzy values, calculated in Eqs. (25) and (26):

V ($S_{c1} \geq S_{c2}$) = 0,66   V ($S_{c2} \geq S_{c1}$) = 1
V ($S_{c1} \geq S_{c3}$) = 0,63   V ($S_{c2} \geq S_{c3}$) = 0,98
V ($S_{c1} \geq S_{c4}$) =0,40   V ($S_{c2} \geq S_{c4}$) = 0,77
V ($S_{c1} \geq S_{c5}$) =0,77   V ($S_{c2} \geq S_{c5}$) = 1
V ($S_{c1} \geq S_{c6}$) = 0,37   V ($S_{c2} \geq S_{c6}$) = 0,74
V ($S_{c1} \geq S_{c7}$) = 0,32   V ($S_{c2} \geq S_{c7}$) = 0,70

V ($S_{c3} \geq S_{c1}$) = 1   V ($S_{c4} \geq S_{c1}$) = 1
V ($S_{c3} \geq S_{c2}$) = 1   V ($S_{c4} \geq S_{c2}$) = 1
V ($S_{c3} \geq S_{c4}$) = 0,78   V ($S_{c4} \geq S_{c3}$) = 1
V ($S_{c3} \geq S_{c5}$) = 1   V ($S_{c4} \geq S_{c5}$) = 1
V ($S_{c3} \geq S_{c6}$) = 0,76   V ($S_{c4} \geq S_{c6}$) = 0,98
V ($S_{c3} \geq S_{c7}$) = 0,72   V ($S_{c4} \geq S_{c7}$) = 0,95
V ($S_{c5} \geq S_{c1}$) = 1   V ($S_{c6} \geq S_{c1}$) = 1
V ($S_{c5} \geq S_{c2}$) = 0,92   V ($S_{c6} \geq S_{c2}$) = 1
V ($S_{c5} \geq S_{c3}$) = 0,90   V ($S_{c6} \geq S_{c3}$) = 1
V ($S_{c5} \geq S_{c4}$) = 0,72   V ($S_{c6} \geq S_{c4}$) = 1
V ($S_{c5} \geq S_{c6}$) = 0,70   V ($S_{c6} \geq S_{c5}$) = 1
V ($S_{c5} \geq S_{c7}$) = 0,66   V ($S_{c6} \geq S_{c7}$) = 0,97

V ($S_{c7} \geq S_{c1}$) = 1
V ($S_{c7} \geq S_{c2}$) = 1
V ($S_{c7} \geq S_{c3}$) = 1
V ($S_{c7} \geq S_{c4}$) = 1
V ($S_{c7} \geq S_{c6}$) = 1
V ($S_{c7} \geq S_{c7}$) = 1

Based on the calculations in Eqs. (28) and (29), the weight vector W ' is thus:

d(C1) = V ($S_{c1} \geq S_{c2}, S_{c3}, S_{c4}, S_{c5}, S_{c6}, S_{c7}$)
=min (0.66, 0.63, 0.40, 0.77, 0.37, 0.32) = 0.32
d(C2) = V ($S_{c2} \geq S_{c1}, S_{c3}, S_{c4}, S_{c5}, S_{c6}, S_{c7}$)
=min (1, 0.98, 0.77, 1, 0.74, 0.70) =0.70
d(C3) = V ($S_{c3} \geq S_{c1}, S_{c2}, S_{c4}, S_{c5}, S_{c6}, S_{c7}$)
=min (1, 1, 0.78, 1, 0.76, 0.72) = 0.72
d(C4) = V ($S_{c4} \geq S_{c1}, S_{c2}, S_{c3}, S_{c5}, S_{c6}, S_{c7}$)
=min (1, 1, 1, 1, 0.98, 0.95) = 0.95
d(C5) = V ($S_{c5} \geq S_{c1}, S_{c2}, S_{c3}, S_{c4}, S_{c6}, S_{c7}$)
=min (1, 0.92, 0.90, 0.72, 0.70, 0.66) = 0.66
d(C6) = V ($S_{c6} \geq S_{c1}, S_{c2}, S_{c3}, S_{c4}, S_{c5}, S_{c7}$)
=min (1, 1, 1, 1, 1, 0.97) = 0.97
d(C7) = V ($S_{c7} \geq S_{c1}, S_{c2}, S_{c3}, S_{c4}, S_{c5}, S_{c5}$)
=min (1, 1, 1, 1, 1, 1) = 1

therefore

w' = $(0.32, 0.7, 0.72, 0.95, 0.66, 0.97, 1)^T$

via normalization, and we have obtained the weight vectors with respect to the decision criterion $C_1, C_2 \ldots\ldots C_7$:

w= $(0.059, 0.132, 0.135, 0.177, 0.123, 0.182, 0.193)^T$

The arithmetic mean of the judgements was used to aggregate these fuzzy values; we give example of alternative ratings for criteria C1 in table 10.

At the second level of the decision procedure, the experts compare alternatives A l, A 2 ……A7 under each of the criteria separately. 7 deferent table were obtaining, we shown 2 table that represent the result of comparison of alternatives under criteria 1 and 2. after that we use the same step used to calculate the vector weight vector for the decision criteria.

Table 10. Fuzzy experts' alternative ratings for criteria C1.

1. C1	A1	A2	A3	A4	A5	A6	A7	A8	wc
A1	(1.00, 1.00, 1.00)	(3.00, 5.00, 7.00)	(1.00, 3.00, 5.00)	(0.33, 1.00, 1.00)	(0.33, 1.00, 1.00)	(0.20, 0.33, 1.00)	(3.00, 5.00, 7.00)	(3.00, 5.00, 7.00)	0,17
A2	(0.14, 0.20, 0.33)	(1.00, 1.00, 1.00)	(0.20, 0.33, 1.00)	(0.14, 0.20, 0.33)	(0.20, 0.33, 1.00)	(0.20, 0.33, 1.00)	(0.33, 1.00, 1.00)	(0.33, 1.00, 1.00)	0,03
A3	(0.20, 0.33, 1.00)	(1.00, 3.00, 5.00)	(1.00, 1.00, 1.00)	(0.33, 1.00, 1.00)	(0.20, 0.33, 1.00)	(0.20, 0.33, 1.00)	(3.00, 5.00, 7.00)	(3.00, 5.00, 7.00)	0,15
A4	(1.00, 1.00, 3.00)	(3.00, 5.00, 7.00)	(1.00, 1.00, 3.00)	(1.00, 1.00, 1.00)	(0.33, 1.00, 1.00)	(0.33, 1.00, 1.00)	(3.00, 5.00, 7.00)	(1.00, 3.00, 5.00)	0,24
A5	(1.00, 1.00, 3.00)	(1.00, 3.00, 5.00)	(1.00, 3.00, 5.00)	(1.00, 1.00, 3.00)	(1.00, 1.00, 1.00)	(1.00, 3.00, 5.00)	(3.00, 5.00, 7.00)	(3.00, 5.00, 7.00)	0,17
A6	(1.00, 3.00, 5.00)	(1.00, 3.00, 5.00)	(1.00, 3.00, 5.00)	(1.00, 1.00, 3.00)	(0.20, 0.33, 1.00)	(1.00, 1.00, 1.00)	(3.00, 5.00, 7.00)	(3.00, 5.00, 7.00)	0,17
A7	(0.14, 0.20, 0.33)	(1.00, 1.00, 3.00)	(0.14, 0.20, 0.33)	(0.14, 0.20, 0.33)	(0.14, 0.20, 0.33)	(0.14, 0.20, 0.33)	(1.00, 1.00, 1.00)	(0.33, 1.00, 1.00)	0,03
A8	(0.14, 0.20, 0.33)	(1.00, 1.00, 3.00)	(0.14, 0.20, 0.33)	(0.20, 0.33, 1.00)	(0.14, 0.20, 0.33)	(0.14, 0.20, 0.33)	(0.20, 0.33, 1.00)	(1.00, 1.00, 1.00)	0.04

Table 11. Global performance of alternatives and outrankin

FINAL SCORE	A1	A2	A3	A4	A5	A6	A7	A8
	0,162	0,118	0,143	0,112	0,107	0,093	0,130	0,135
Rank	1	5	2	6	7	8	4	3

5.3 A comparison between the FTOPSIS and FAHP methods:

5.3.1 Correlation coefficients

Table 12. Rank of alternatives by FTOPSIS and FAHP

Alternatives	Fuzzy Topsis		Fuzzy AHP	
	cci	Rank	cci	Rank
A1	0,600	1	0,162	1
A2	0,45	5	0,118	5
A3	0,59	2	0,143	2
A4	0,426	6	0,112	6
A5	0,36	8	0,107	7
A6	0,422	7	0,093	8
A7	0,57	4	0,130	4
A8	0,58	3	0,135	3

Correlation coefficients facilitate the comparison of data and assess their similarity. This research compares ranking lists derived using FTOPSIS and FAHP utilizing the Spearman rank correlation coefficient [54].

- **Spearman's rank correlation coefficient**

Calculate the Rank Differences:

For each alternative i, calculate the difference between its rank in Fuzzy AHP $R_{Fuzzy\ AHP,i}$ and its rank in Fuzzy TOPSIS $R_{Fuzzy\ TOPSIS,i}$

$d_i = R_{Fuzzy\ AHP,i} - R_{Fuzzy\ TOPSIS,i}$

d_i^2 Square each rank difference:

Calculate Spearman's Rank Correlation Coefficient:

Apply the formula for Spearman's Rank Correlation Coefficient ρ:

$\rho = 1 - \frac{6 - \sum d_i^2}{n(n^2-1)} = 1 - \frac{6-2}{8(64-1)} = 0.996$

Where:

$-\ d_i$ is the difference in ranks for each alternative.

n is the total number of alternatives.

From the result obtained from the Spearman test, we conclude that there is a very strong relationship between the Fuzzy AHP method and Fuzzy Topsis method in arranging technologies.

5.3.2 Sensitivity Analysis:

Sensitivity analysis is used to assess the stability of the results over a wide range of input variable values, we used it to assess how variations or changes in weights of particular criteria impact the robustness of the rankings.

- **For Fuzzy Topsis Methode:**

It consists of 21 scenarios in which the criteria's values are changed. Each scenario involves the replacement of user weights for two Criteria. For instance, in Scenario c1-c2, the weights of Criteria 1 and Criteria 2 have been swapped. Results obtained for all alternatives are presented in figure 01.

According to the sensitivity study results, changing the criterion weights has little effect on the IoT. When all possibilities have been reviewed, it is the best alternative, as seen in Figures 11. When the weights of the assessment criteria were altered, the Internet of Things (IoT) maintained its position in 16 scenarios and had the highest CCi score in the original condition. In the majority of scenarios, artificial intelligence receives the second-highest score, ranked first 5 times, occupied second place ten times, and third place four times.

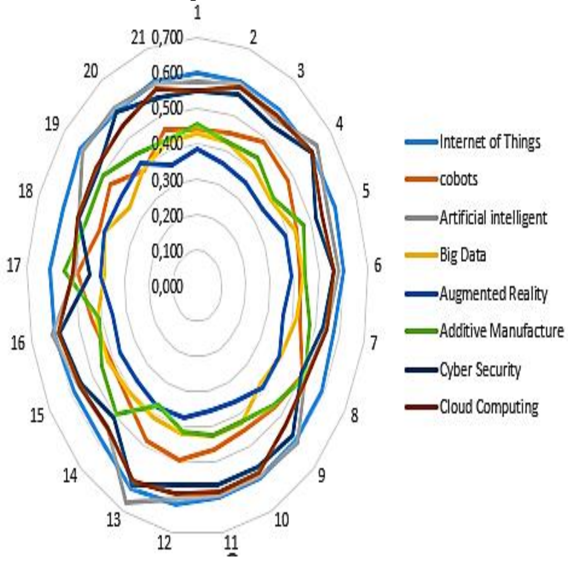

Figure 11.Sensitivity Analysis for Fuzzy Topsis Method

- **For Fuzzy AHP Methode:**

It consists of 21 scenarios in which the criteria's values are changed. Each scenario involves the replacement of user weights for two Criteria. For instance, in Scenario c1-c2, the weights of Criteria 1 and Criteria 2 have been swapped. Results obtained for all alternatives are presented in figure 12.

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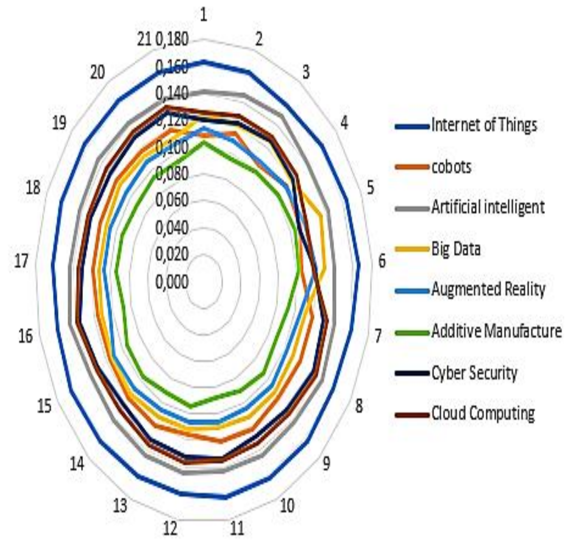

Figure 12. Sensitivity Analysis for Fuzzy AHP Method

5.3.3 Computational complexity

When assessing the computational complexity of competing approaches, only the time complexity was taken into account. Similar to Chang [54], the number of time multiplications performed inside the algorithms was used to assess the time complexity, T. Furthermore, logical operations and exponentiation were used in this study as markers of times complexity. considering that m criteria and n alternative providers exist. The normalised decision matrix, weighted decision matrix, and distances d+i and d−i must be calculated using 3nm operations, 3nm operations, and 14nm operations, respectively, in order to use the FTOPSIS approach. The FTOPSIS method's times complexity, Tn,m, is thus given by Eq. (31).

$$T_{n,m} = 3nm + 3nm + 7nm + 7nm = 20nm \quad (31)$$

= 1120 operations

In order to calculate the degrees of possibility, normalize the vector W, compute the fuzzy synthetic extent to all the decision matrices, and finally compute the global performance, the Fuzzy AHP method, following the same methodology, needs nm (n − 1) + n (n − 1) operations. It then takes n(m+1) to execute the normalization process. Hence, the temporal complexity, T'n,m, of the fuzzy AHP algorithm is given by Eq. (32) [55].

$$T_{n,m} = 6m (n + 1) + nm (n − 1) + n(n − 1) + n (m + 1) + nm$$

$$= n^2(m + 1) + m (7n + 6) \quad (32)$$

$$= 8*8(8) +8(7*8+6) =1008$$

Figure 13 and 14 displays the time complexity variation for both methods for varying numbers of criteria as a function of the number of alternatives. Overall, it is evident that FAHP outper forms FTOPSIS. In the application scenario, the FAHP approach used 1008 operations, but the Fuzzy TOP-SIS method needed 1120.

The standards Within the framework of the FTOPSIS technique, there are no restrictions placed on the number of options or criteria that are utilized in the selection process. Based on the comparative analysis of the FAHP technique, there are some restrictions placed on the amount of criteria and options that can be considered. According to Saaty [56], it is recommended that the number of criteria or possibilities for comparison utilizing FAHP be limited to nine in order to maintain the consistency of human judgment. The FAHP technique follows this recommendation in the same way that it does anything else. The application scenario, which consisted of seven criteria and eight choices, provided evidence that the FAHP technique could be successfully implemented. The amount of alternatives is a severe limitation, despite the fact that the constraint on the number of criteria can be alleviated by implementing the criteria inside the framework of the FAHP hierarchical structure. Consequently, the selection of the technique is contingent upon the specifics of the number of alternatives and criteria; for instance, if we posit the existence of more than nine Industry 4.0 technologies (alternatives), then employing FTOPSIS would be preferable to the FAHP approach.

Fuzzy AHP is computationally intensive, particularly as the number of criteria grows due to pairwise comparisons. It is better suited for problems with fewer criteria and alternatives, where decision-makers value consistency and depth of analysis. On the other hand, Fuzzy TOPSIS is more efficient and appropriate for larger datasets or applications with multiple criteria and alternatives that require computational efficiency. See figure 15.

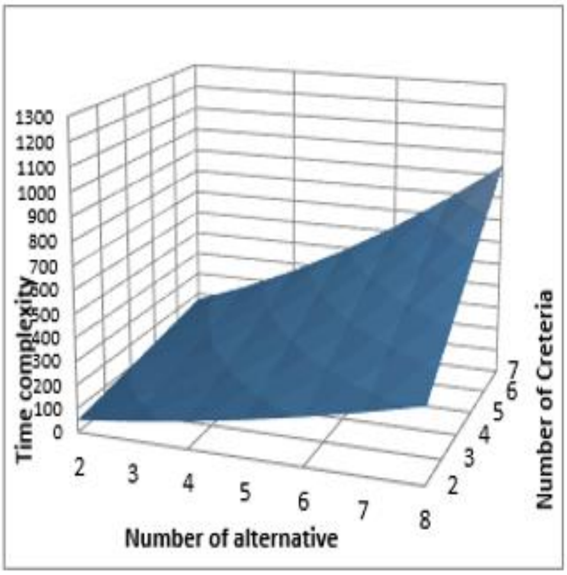

Figure 13. Time complexity for 8 technologies and 7 challenges For Fuzzy AHP Methode

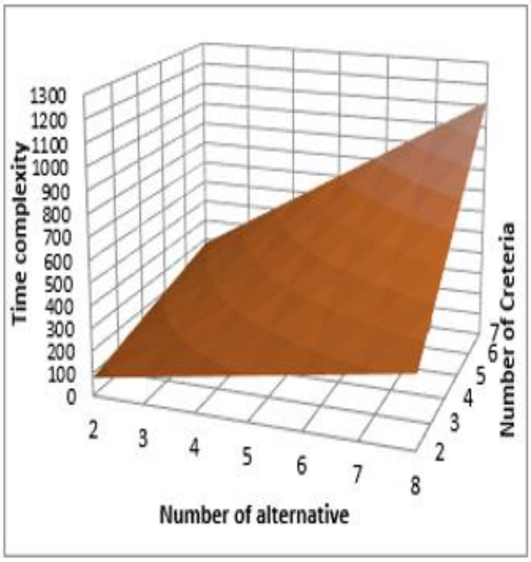

Figure 14. Time complexity for 8 technologies and 7 challenges For Fuzzy Topsis Methode

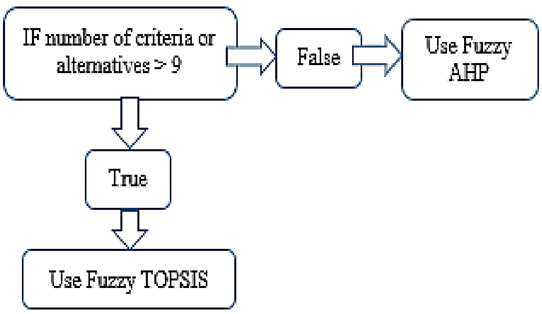

Figure 15. Use case comparison between fuzzy AHP and Fuzzy TOPSIS

6. Design Phase:

N'gaous, renowned for its agricultural production, particularly in the fruit sector (such as apricots and apples), could benefit from the Internet of Things to improve its industrial and agricultural processes.

6.1. Examples of application of IoT technology in N'gaous factory:

- **Cold chain management for fruits.**

For example, humidity and temperature sensors in warehouses and delivery trucks.

application: Because fruits like apricot and orange are sensitive to temperature and humidity, IoT sensors make sure that the best conditions are met for storage and shipping, keeping the goods fresh until they get to their destination.

- **Energy Management for Transformation Facilities**

For example, Monitoring energy consumption in food processing plants.

Application: IoT sensors identify energy consumption peaks, allowing optimization of the use of energy-consuming equipment and reduction of energy costs.

- **Production Equipment Monitoring**

An illustration of this is the integration of IoT sensors into fruit processing machines, such as peelers, crushers, and canning machines.

Application: By monitoring the status of equipment, anticipating potential breakdowns, and planning maintenance, these sensors prevent costly production shutdowns.

- **Product Traceability**

For example, sensors are connected to RFID or QR labels to monitor the movement of products from the field to the point of sale.

Application: Enhances consumer confidence and transparency by guaranteeing the traceability of processed products and fruits, and enables more effective management of product recalls in the event of a need.

- **Predictive Maintenance of Processing Machines**

For example, the installation of IoT sensors on machines to monitor temperature, vibrations, and wear.

Application: The data collected can be analyzed to predict the maintenance needs of machines in advance, thereby ensuring continuous production and reducing repair costs.

Figure 16 represent some proposed application of IOT in N'gaous Factory

6.2. Examples of application of artificial intelligence technology in N'gaous factory:

Implementing AI in N'gaous factory could transform the local economy by increasing efficiency, reducing costs, and improving the quality of agricultural products. By integrating these advanced technologies, N'gaous could position itself as a competitive player in the agro-industrial sector. Integrating AI into a N'gaous factory, especially in industry and transportation, can provide significant benefits in improving production, efficiency and product quality. Thus, AI can:

- **Improve harvesting and logistics**

For example: AI algorithms that improve transportation logistics and harvest planning like K-Means and DBSCAN (Density-Based Spatial Clustering) for Hub and Distribution Optimization.

Application: Ai helps in determining the ideal harvest times based on the maturity of the fruits and effectively planning transportation routes for delivery using a logistics application studied with efficient algorithms, thus reducing the losses of perishable products.

- **Automated sorting and grading of products**

For example, we propose the use of AI vision systems in processing facilities to sort fruits by color, size and quality. Application: These automated systems facilitate fast and accurate sorting, thus ensuring product consistency and reducing labor costs, this sorting is very important for the N'qaous factory.

- **Predictive maintenance of equipment**

For example, we propose using AI to monitor the operating data of squeezing and filtering machines Application: AI predicts equipment failures by examining wear indicators, thus enabling producers to organize maintenance before a costly breakdown occurs, which leads to ensuring uninterrupted productivity.

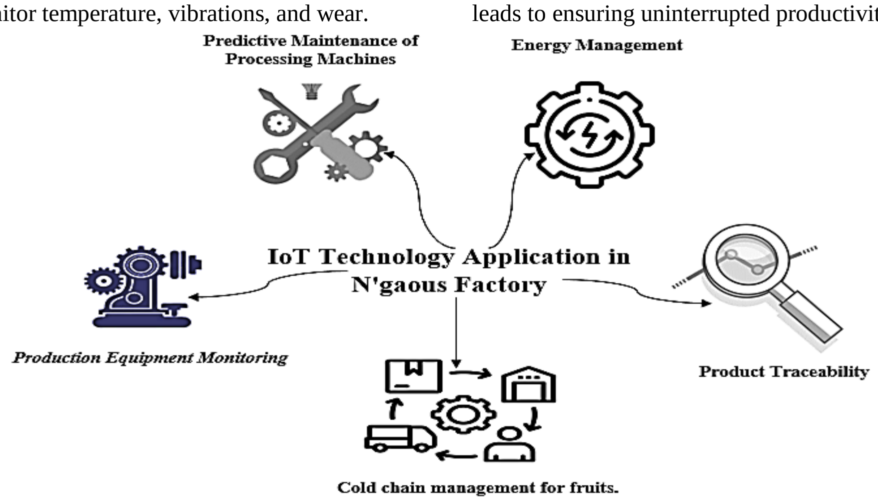

Figure 16. Proposed application of IOT in N'gaous Factory

- **Forecasting Market Demand and Price**

For instance, artificial intelligence models are employed to forecast the price trends of fruits.

Application: These models enable farmers and distributors in N'gaous to optimize profits by adjusting their production and sales strategies in response to historical data and market analysis, thereby preventing surpluses or shortages.

- **Automation of Food Processing Processes**

Example: The use of artificial intelligence to automate and optimize production lines in fruit processing plants. Application: Artificial intelligence algorithms analyse and modify production processes (such as washing, cutting, and canning) in real time, thereby enhancing the efficiency and precision of operations and decreasing waste.

6.3. Examples of application of cloud computing technology in N'gaous factory:

Ngaous factory could use cloud computing to streamline and modernize its manufacturing operations. Figure 18 represent some proposed application of cloud computing for N'gaous Factory.

illustrates some specific uses of cloud computing that could benefit this facility:

- **Inventory and Production Management:**

Example: N'gaous factory can track production status in real time using a cloud system-based production management. managers have remote access to centralized data on inventory levels and production numbers. ability to better allocate resources, anticipate stockouts, and adapt output to meet demand is a key benefit of this monitoring system.

- **Quality Control in Real-Time:**

The plant may track product quality characteristics (such as temperature, humidity, and acidity for juices) by connecting quality control sensors to the cloud. This allows for continuous monitoring throughout the manufacturing process. Any discrepancies in this data are immediately identified by automated analysis.

-Advantage: Rapid detection of anomalies improves product quality, reduces waste, and ensures consistent adherence to quality standards.

- **Supply Chain Optimization**

Application: N'gaous factory may track the movement of raw materials and completed goods by integrating a cloud-based logistics management system. This improves the supply chain. Suppliers and distributors are kept informed of inventory and delivery details in real time. Faster delivery times, and Lower logistics costs are all benefits of improved visibility, which in turn leads to a more efficient supply chain.

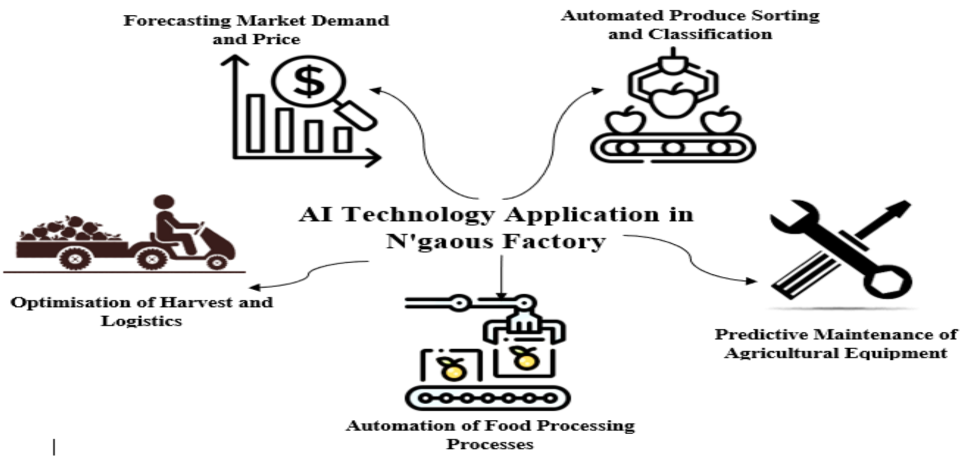

Figure 17. Proposed application of AI in N'gaous Factory

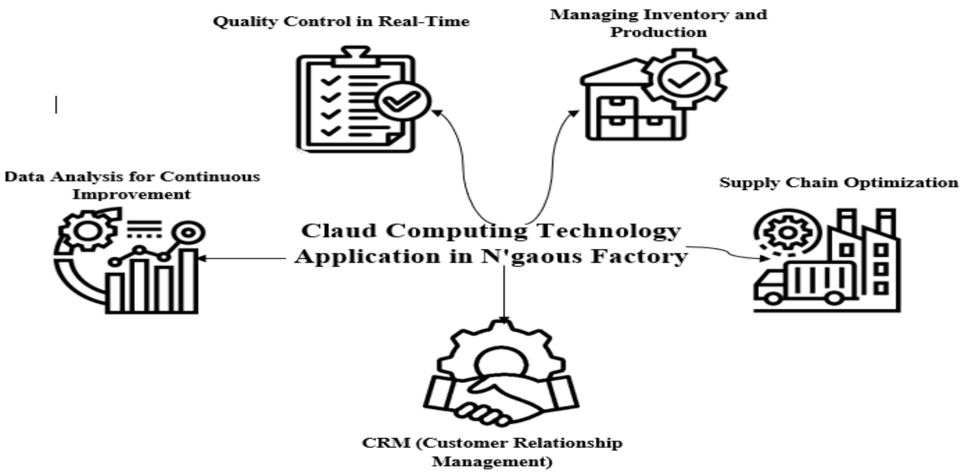

Figure 18. Proposed application of Cloud computing in N'gaous Factory

- **CRM (Customer Relationship Management)**

  Use Case: Cloud-based CRM system allows better communication with customers by collecting customer data, purchase history and service requests, factory sales staff have access to real-time data.

  Benefit: Increase customer satisfaction through fast service and better meeting market demands.
- **Data analysis for continuous improvement**

  Use Case: By collecting and analyzing all sales, logistics, manufacturing and maintenance data on a cloud platform, N'gaous factory can improve operations and anticipate demand changes.

  Benefit: N'gaous Factory can make better decisions and enhance its operations to stay competitive using in-depth data analysis.

7. Verify Phase

In this Phase we use the Factory I/O simulator software is an essential instrument in the Verify Phase, offering a regulated virtual setting for the thorough testing, validation, and optimization of process designs prior to real implementation. The software's capability for real-time simulation, control integration, and data collecting support DFSS's focus on accuracy and continuous enhancement, hence improving the dependability and quality of the final production process. The Verify Phase in Design for Six Sigma (DFSS) and the Factory I/O simulator software intersect significantly when validating and refining manufacturing processes in an industrial setting. We use this software on the most rated technology by the expert "IoT".

This is an example of using the software on the most influential technology on N’gaous factory “Internet of Things”. In our virtual factory, we used IoT sensors with the same characteristics offered by the software Factory IO. See figure 19.

we use:

- **Capacitive sensors:** Among their uses are monitoring production equipment due to their ability to detect material properties, environmental 7conditions, and distances. They can also track changes in equipment, such as thinning or deformation of machine parts. By detecting small changes in equipment geometry, they enable predictive maintenance, reducing the risk of unexpected equipment downtime and ensuring the reliability of production lines. Capacitive sensors can be used to detect humidity and moisture levels in production environments that can affect the company’s fruits, such as apricots and oranges.
- **Diffuse sensors:** These sensors detect objects or materials based on the reflection of the emitted light, allowing them to perform various tasks without the need for a reflector. In inventory management, diffuse sensors can detect the presence or absence of items on storage shelves. By connecting these sensors, N’gaous Factory can track inventory in real time, ensuring better management of inventory levels and reducing sudden stockouts.

Figure 19. Representation of N’gaous factory by Factory IO software

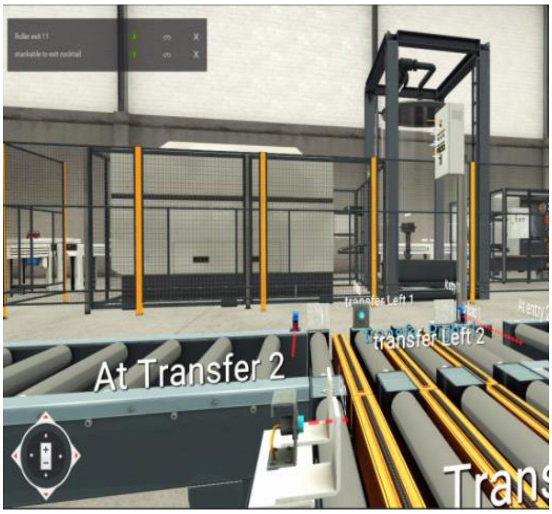

Figure 20. Figure show the representation of diffuse sensors in N’gaous factory

- **Vision sensors:** Capture images and process visual data in real time, allowing machines to “see” and interpret their environment. In the context of Industry 4.0, vision sensors facilitate the provision of accurate and reliable data, which is analyzed and used for decision-making. Vision sensors provide guidance to robots. They provide visual and spatial information that is detected over a range of 0.3 to 3 meters, allowing them to recognize, select and place objects with high accuracy. In an IoT ecosystem, this data enables better coordination across automated systems, facilitating a higher level of accuracy in complex assembly or packaging operations in N’gaous factory.

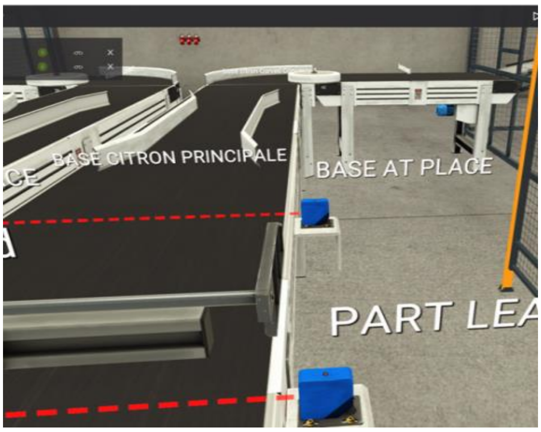

Figure 21. Figure show the representation of vision sensors in N'gaous factory

In this phase we used un example of haw factory IO software can offering a regulated virtual setting for N'gaous factory, Factory IO encapsulates the other technologies of Industry 4.0 that we defined in our paper , including , Robotics , cloud computing, Artificial Intelligence ,data analytics, and Augmented Reality .It provides an immersive environment for users to model, simulate, and test Industry 4.0 applications before implementation, making it a valuable tool for training, system design, and verify in smart manufacturing contexts.

8. Discussion:

The Design for Six Sigma (DFSS) and Multi-Criteria Decision-Making (MCDM) approaches give a formal framework for evaluating Industry 4.0 adoption in manufacturing. This strategy guides stakeholders through define, measure, analyse, design, and verify to match technical decisions with strategic and operational goals. MCDM approaches enable technology 4.0 prioritisation over cost, compatibility, and other challenges, deepening the decision-making process. Simulation tools like Factory IO in the verification phase are a great complement to this system. Virtual modelling and testing in a controlled digital environment let organisations visualise and analyse new technology integration before physical installation. This procedure greatly eliminates costly mistakes. Despite its strengths, the proposed framework is not without limitations. A key concern is the limited number of experts involved in the decision-making process. MCDM relies on expert judgement to weigh and assess criteria, therefore a small or imbalanced expert panel may restrict the viewpoint and reduce robustness and impartiality. Scalability is another issue. DFSS-MCDM works well in targeted or small-scale applications but may struggle in big, diversified, or multi-site industrial environments. The framework provides a promising and structured approach for digital transformation planning, but future research on expert diversity, bias-reduction, and scalability is needed to expand industrial adoption.

9. Conclusion:

The integration of the Design for Six Sigma (DFSS) approach with multi-criteria decision-making (MCDM) methods offers a robust framework for the pre-implementation assessment of Industry 4.0 technologies in manufacturing industries. By systematically guiding decision-makers through each phase—define, measure, analyze, design, and verify—this combined methodology ensures a thorough evaluation that aligns with organizational objectives while addressing both technical and financial feasibility. MCDM enhances this process by allowing a structured prioritization of multiple criteria, helping managers to balance aspects like cost, integration complexity, and technological capability to make informed choices on Industry 4.0 technologies. In the final verification phase, incorporating tools like Factory IO software can be transformative. As a virtual simulation platform, Factory IO enables users to model and test Industry 4.0 technologies in a controlled environment, simulating real-world scenarios within a digital factory setup. This addition helps validate the performance, and interoperability of the selected technologies before actual implementation, mitigating risks and identifying potential issues early. Overall, this approach enhances the precision, and quality of Industry 4.0 technology adoption in manufacturing, ensuring that organizations are well-prepared for successful digital transformation.

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