# A Picture Fuzzy Decision-Making Framework for COBOT Selection in Digital Supply Chains

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**INFORMATION**

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**ABSTRACT**

Driven by digitalization in supply chains, the use of Collaborative Robots (COBOTs) has become increasingly widespread in recent years. They significantly contribute to process efficiency by working in place of, or in collaboration with, humans in a variety of operations, including welding, painting, assembly and disassembly, transportation, packaging, and palletizing. However, when uncertainty and different criteria are taken into account, decision support systems that compare practical robots based on their suitability for specific needs are inadequate. This study presents a comprehensive multi-criteria decision-making (MCDM) framework for prioritizing COBOTs with different features used in digital supply chain processes. Based on in-depth research in the literature and the opinions of experts working in companies that use relevant robots in the industry, the criteria to be evaluated when selecting COBOT types are identified. The importance of these criteria was determined using the Picture Fuzzy Step-wise Weight Assessment Ratio Analysis (PiF-SWARA) method, which effectively captures the uncertainty in experts' decision-making processes. Subsequently, alternative COBOT types were ranked using the Picture Fuzzy Combinative Distance-Based Assessment (PiF-CODAS) approach. This case study, which evaluates the PiF-SWARA-CODAS concept, reveals that according to expert assessments, cost is the most important criterion in COBOT selection, followed by process quality and space utilization. The findings about the selection of types emphasize that high-efficiency articulated robots operating at high speeds under mass production conditions are the primary priority. These robots are followed by humanoid robots. The third most important are power and force-limiting robots. The fourth and fifth types of COBOTs are hand-guided and safety-monitored stop robots. Validation and sensitivity analyses confirmed the robustness of the results. Overall, the proposed framework not only clarifies the key priorities for manufacturing facilities but also provides a validated decision support tool to align digitalization strategies with the most appropriate COBOT investments.

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## 1 Introduction

Industrial robots are used to eliminate human error, increase efficiency, ensure work safety in potentially hazardous situations, and design fully automated systems, particularly in processes such as manufacturing and assembly. Research in human-robot collaboration is becoming more and more necessary as a result of the field's high level of interest in industrial applications. Human capabilities such as sensitivity, dexterity, and problem-solving can be effectively combined with the strength, precision, and speed of robotic systems. This synergy enhances both the performance and flexibility of production processes [1]. A Collaborative Robot (COBOT) is a vital tool for various industrial applications, including material handling, assembly, finishing, machine loading, spray painting, and welding, due to its decision-making capabilities, ability to react to diverse sensory inputs, and capacity to interface with other machines [2]. The majority of commercial robot applications have very limited capacity to physically engage and interact with humans, and today's industrial robots are still largely pre-programmed to execute certain tasks. Therefore, developing different components of COBOT systems that allow humans to perform jobs that are too challenging for robots is of great importance [3]. A collaborative application is the whole configuration of a COBOT, gripper, and workspace to carry out a particular task in conjunction with a human [4]. Because there are so many different types of robots available, it can be challenging to select the best one for a given industrial need. Industrial robots offer a wide range of capabilities and requirements for an application [2]. Finding the optimal MCDM methodology requires considering the right criteria and alternatives for a specific robot. The relative performance and rankings of robots in industrial pick-and-place tasks can then be evaluated using MCDM methods [5]. Therefore, it has become an important question as to which robot applications, which are quite costly, should be prioritized for investment by businesses. By selecting the type of application that will improve business efficiency optimally, competitiveness can be increased.

This study aims to evaluate COBOT types that contribute significantly to process improvement through the digitalization of supply chains using MCDM techniques. Based on an in-depth literature review, particularly on COBOT types that have become more popular with the human-machine collaboration introduced by Industry 5.0 (I5.0), the robot types used were determined as alternatives. When determining alternatives, in addition to the COBOT types defined in ISO/TS 15066:2016 [6], those found in the literature were also included to create a unique alternative structure. During the process of identifying alternatives, the opinions of experts were also taken into account, ensuring that the types commonly used in the industry were considered. Expert assessments of the types defined in ISO/TS 15066:2016 were also included in the scope of the study. In addition, sources relevant to the study were searched in the literature [7–9]. Criteria for determining suitable robot alternatives for companies, particularly in production and assembly processes, have been defined. These criteria have been compared according to their importance levels and weighted accordingly. The following sections have explained the specifics and steps of the Picture Fuzzy SWARA (PiF-SWARA) approach, which was used to determine the criterion weights after the previously defined standards were thoroughly examined and the opinions of relevant experts were taken into consideration. After weighing the criteria, the alternatives used in the COBOT type selection process were prioritized using the Picture Fuzzy Criteria Importance Through Intercriteria Correlation (PiF-CODAS) approach. Multi-criteria methods commonly used in the literature for prioritizing COBOT types were examined in depth. CODAS, one of the innovative and unstudied methods introduced in recent years in related fields, was chosen for this purpose. The study evaluated the results using fuzzy decision-making to better model decision-makers' opinions. Picture fuzzy sets, which are both previously unstudied and relatively innovative, were also used in fuzzy decision-making approaches. Because MCDM analysis enables the efficient examination of numerous factors at once, it was preferred in this study. In the following ways, the study significantly adds to the body of literature:

i) The picture fuzzy PiF-SWARA-CODAS approach was used for the first time together to provide a fuzzy decision-making methodology. This methodology has adopted the new hybrid MCDM concept to prioritize COBOT types in an uncertain environment with PiF extensions.

ii) For the first time, a case study containing practical evaluations to support human-machine collaboration, a relatively new idea introduced with I5.0 in supply chains, has been presented. The results of the study have been examined in detail.

iii) This study is the first article to evaluate COBOT types by also considering the needs of supply chains.

The sections of the article are organized as follows. The literature review for this study is presented in Section 2. The preliminary information on fuzzy clusters is explained in detail in Section 3. The proposed methodology is discussed in Section 4, and the case study is addressed in Section 5. The discussion section is outlined in Sections 6, and 7 includes the results and recommendations for future applications.

## 2 Literature Review

An extensive literature review was conducted to examine previous research on COBOT applications in the supply chain, to identify evaluation criteria and alternatives for this study, and to highlight the originality of this study. The concept of COBOT was included in books, journals and conference proceedings accessible through the SCOPUS database. However, the literature search with the related keyword found too many studies. Therefore, the scope was further customized to include different types of COBOT models that can be used throughout the supply chain. To make the literature review process more systematic, the PRISMA methodology, which stands for "Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)", was used. The PRISMA approach, designed by Moher et al. [10], has become widely used among academics in recent years. Sources are analyzed and evaluated according to the determined eligibility criteria. Then, appropriate studies are selected. Table 1 lists the keywords used to perform a PRISMA method literature review, along with the number of studies found using these keywords.

**Table 1:** Literature search with keywords

| Keywords | # of paper |
|---|---|
| TITLE-ABS-KEY ("cobot") | 1107 |
| (TITLE-ABS-KEY ("cobot") AND TITLE-ABS-KEY ("criteria")) | 38 |
| (TITLE-ABS-KEY ("cobot") AND TITLE-ABS-KEY ("select")) | 13 |
| (TITLE-ABS-KEY ("cobot") AND TITLE-ABS-KEY ("fuzzy")) | 14 |
| (TITLE-ABS-KEY ("cobot") AND TITLE-ABS-KEY ("multi criteria decision making") | 7 |
| (TITLE-ABS-KEY ("cobot type") AND TITLE-ABS-KEY ("select")) | 0 |

A total of 1179 studies were found in SCOPUS after searching with the keywords shown in Table 1. When the keyword "COBOT" was searched with "select," 13 results were obtained, and when searched with "fuzzy," 14 results were obtained. Since we searched the concept of COBOT broadly, many studies were found. The results were duplicated because some keywords appeared repeatedly in the search. Research was also conducted to limit the study to the selection of COBOT types. The total number of papers evaluated was reduced to 17 once the SCOPUS search was finished because studies written in languages other than English, studies that were not fully accessible, and studies that did not clearly express the methodology or results were all removed. Table 2 lists these studies' contributions to the body of literature. The goal of this literature review was to draw attention to how unique and novel our suggested framework is.

**Table 2:** Summary of literature review

| # | Author(s) | Adopted method(s) | Aim |
|---|---|---|---|
| 1 | Dei et al. (2025) [11] | A survey study | Explains how a multimodal feedback system called (A)MICO was planned, developed, and tested. It has both visual and aural input and is intended to help workers communicate with COBOT on production lines. |
| 2 | Silva et al. (2024) [12] | A qualitative study | States to develop a decision-making framework for COBOT adoption in manufacturing companies. |
| 3 | Sivalingam and Subramaniam (2024) [2] | Analytic Hierarchy Process (AHP)—Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) | Approaches for selecting the most appropriate COBOTs for fuel filter assembly operation. |
| 4 | Keshvarparast et al. (2024) [13] | Literature review | Examines how integrating COBOTs into assembly and disassembly lines affects output. |
| 5 | Chatterjee et al. (2024) [14] | Logarithmic percentage change-driven objective weighting (LOPCOW) and ordering preference targeting at bi-ideal average solutions (OPTBIAS) | Elfin-P is the best appropriate COBOT model for the assembly procedure under consideration, according to the OPTBIAS approach, which is based on a real-time illustrative case with 13 choices and 6 evaluation criteria. |

(Continued)

**Table 2 (continued)**

| # | Author(s) | Adopted method(s) | Aim |
|---|---|---|---|
| 6 | Liu et al. (2024) [15] | Literature review | To improve comprehension of the use of COBOTS in manufacturing, the implications of COBOTs on ergonomics, productivity, task scheduling, safety, system design, and workspace design are examined. |
| 7 | Palanikumar et al. (2023) [8] | log Fermatean vague normal weighted averaging (log FVNWA), logarithmic Fermatean vague normal weighted geometric (log FVNWG), log generalized Fermatean vague normal weighted averaging (log GFVNWA) and log generalized Fermatean vague normal weighted geometric (log GFVNWG) | Aims to select robots for the field of agricultural robotics. |
| 8 | García et al. (2023) [9] | Literature review | Offers a well-organized assessment of the literature on the most recent COBOT applications in service and industrial settings. |
| 9 | Mahanta et al. (2023) [3] | Best Worst Method (BWM) | To evaluate how well industrial COBOTs will work in an industrial workspace, it is aimed to select the most optimal one. |
| 10 | Madzharova-Atanasova and Shakev (2023) [16] | Literature review | The intelligent technologies employed in the robotic systems were analyzed. There is also discussion of the prospects brought about by the advancement of artificial intelligence. |

(Continued)

**Table 2 (continued)**

| # | Author(s) | Adopted method(s) | Aim |
|---|---|---|---|
| 11 | Thongdonnoi et al. (2023) [17] | Exploratory factor analysis (EFA), Confirmatory factor analysis (CFA) & Case Study | Investigations were conducted on the critical aspects that influence the decision to utilize COBOTs in production lines. COBOTs have been demonstrated to increase productivity while decreasing wait times, the number of tasks in line, and the workforce. They can also improve workplace safety and eliminate ergonomic risks for employees. |
| 12 | Görür et al. (2023) [18] | Anticipatory Partially Observable Markov Decision Process (A-POMDP) and Adaptive Bayesian Policy Selection (ABPS) | A framework is proposed to design and evaluate the prediction of short-term human behavior and long-term changing human characteristics. |
| 13 | Moher et al. (2023) [10] | Literature review | Recent COBOT applications in industrial and service contexts. |
| 14 | Silva et al. (2022) [19] | Literature review | Adoption of criteria defining the benefits, advantages and disadvantages of COBOT implementation. |
| 15 | Bozkuş et al. (2022) [20] | Fuzzy Developing Evaluation through Logical Processes of Human Interaction (DELPHI), Decision-Making Trial and Evaluation Laboratory (DEMATEL), Analytic Network Process (ANP), and VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) | Risk analysis is integrated into the fuzzy decision-making process to improve the safety, ergonomics, productivity and quality of the process in human and robot interactions. |

(Continued)

**Table 2 (continued)**

| # | Author(s) | Adopted method(s) | Aim |
|---|---|---|---|
| 16 | Cohen et al. (2022) [21] | Case study | Giving an overview of the key factors pertaining to the purchase and deployment of COBOTs, as well as a productivity analysis process that aids in these decisions. |
| 17 | Rega et al. (2021) [22] | Case study | A facility layout study was conducted to facilitate human-robot interaction work, defining a list of essential components associated with reference norms and production requirements that define collaborative workplaces. |

A comprehensive literature review has been conducted to analyze the research on the evolution and types of robotic applications, one of the important digital revolutions of the supply chain. It is seen that the studies conducted in the relevant field since the first discussion of the COBOT concept until today are mostly based on literature and studies, such as usage areas, ease of use, which are generally evaluated with qualitative approaches rather than quantitative analyses. The fact that the concepts within the scope of the study have started to appear in the literature in recent years can be seen as an explanatory reason, because, in addition to the theoretical evaluation of COBOT applications, it is necessary to make their types and areas of use and basic definitions. For this reason, it is seen that a significant part of the studies is literature research or conceptual framework drawing. No study has used picture fuzzy sets, one of the extended versions of ordinary fuzzy logic, even though fuzzy logic and MCDM methods have been used in studies addressing COBOT applications, which have gained more attention since the introduction of I5.0 and are one of the crucial steps of digital transformation in the supply chain. When examining studies conducted using MCDM, it is observed that innovative methods such as LOPCOW and BWM are used alongside well-known methods such as AHP, TOPSIS, ANP, DEMATEL, and VIKOR. Unlike traditional methods, the innovative SWARA and CODAS methods have therefore been preferred. Additionally, unlike methods that use linear modeling functions such as BWM and FUCOM, these methods were preferred because they are understandable, easily adaptable to real-life problems, and involve less computational complexity.

However, our study's methodology is unique since it combines two powerful MCDM techniques, such as picture SWARA and CODAS. Our approach not only addresses ideas that include COBOT kinds, but it also delivers the first research on the application of effective MCDM approaches in a fuzzy framework, thereby addressing these gaps in the literature. We hope that scholars who are interested in supply chain management process digitization would use our study as a reference.

## 3 Preliminaries of Picture Fuzzy Sets

Cuong and Kreinovich [23] presented the Picture Fuzzy Sets (PiFSs), which extended the intuitionistic fuzzy sets (IFSs) by enabling a more nuanced representation of uncertainty, especially in situations when there are several alternative answers, such as "yes," "no," "abstain," and "reject." IFSs provide several attributes related to modal and topological operators defined over the set of IFSs, as well as operations and relations over sets [24]. PiFSs improve the capacity to handle imprecision and uncertainty by offering operators that expand both fuzzy sets (FSs) and IFSs [25]. By providing a sophisticated way to represent uncertain information in decision-making processes, fuzzy numerical images, or PiFNs, significantly decrease information loss. Based on the responses of decision-makers to four possible solutions, they produce more flexible results than FSs, IFSs, and hesitant fuzzy sets. By including an expanded range of responses, PiFSs extend the theoretical and practical bounds of fuzzy logic and facilitate more thorough and precise decision-making in uncertain situations [26]. Fundamental definitions of PiFs are stated below [23]

A Picture Fuzzy Set (PiFS) $\tilde{X}_a$ over the universe of discourse $U$ is stated as:

**Step 1.** Picture Fuzzy Set (PiFS)

A Picture Fuzzy Set (PiFS) $\tilde{X}_a$ beyond the discourse universe $U$. The definition of $U$ is:

$$\tilde{X}_a = \left\{ \left\langle u, \left( \mu_{\tilde{X}_a}(u), I_{\tilde{X}_a}(u), v_{\tilde{X}_a}(u) \right) \right| u \in U \right\} \tag{1}$$

$\mu_{\tilde{X}_a}(u) : U \rightarrow [0,\ 1]$ defines the degree of membership of $u$ to $\tilde{X}_a$,

$I_{\tilde{X}_a}(u) : U \rightarrow [0,\ 1]$ defines the degree of indeterminacy,

$v_{\tilde{X}_a}(u) : U \rightarrow [0,\ 1]$ defines the degree of non-membership.

$$0 \leq \mu_{\tilde{X}_a}(u) + I_{\tilde{X}_a}(u) + v_{\tilde{X}_a}(u) \leq 1 \forall u \in U \tag{2}$$

The requirement that their sum has to be equal to 1 by these values. The refusal degree $\left(\chi_{\tilde{X}_a}(u)\right)$ is computed below:

$$\chi_{\mathrm{x}_a} = 1 - \left( \mu_{\tilde{X}_a}(u) + v_{\tilde{X}_a}(u) + I_{\tilde{X}_a}(u) \right) \tag{3}$$

**Step 2.** Basic operations of Picture Fuzzy Numbers (PiFNs)

After two PiFNs $\tilde{X}_a = \left(\mu_{\tilde{X}_a}, I_{\tilde{X}_a}, v_{\tilde{X}_a}\right)$ and $\tilde{C}_a = \left(\mu_{\tilde{C}_a}, I_{\tilde{C}_a}, v_{\tilde{C}_a}\right)$ and positive scalar $\lambda$ the related operations are stated [27]

Scalar multiplication:

$$\lambda \cdot \tilde{X}_a = \left\{ \left( 1 - \left(1 - \mu_{\tilde{X}_a}\right)^{\lambda} \right), I^{\lambda}_{\tilde{X}_a}, v^{\lambda}_{\tilde{X}_a} \right\} \tag{4}$$

Exponentiation:

$$\tilde{X}^{\lambda}_a = \left\{ \mu^{\lambda}_{\tilde{X}_a}, I^{\lambda}_{\tilde{X}_a}, \left( 1 - \left(1 - v_{\tilde{X}_a}\right)^{\lambda} \right) \right\} \tag{5}$$

Addition:

$$\tilde{X}_a \oplus \tilde{C}_a = \{\mu_{\tilde{X}_a} + \mu_{\tilde{C}_a} - \mu_{\tilde{X}_a}\mu_{\tilde{C}_a}, I_{\tilde{X}_a}I_{\tilde{C}_a}, v_{\tilde{X}_a}v_{\tilde{C}_a}\} \tag{6}$$

Multiplication:

$$\tilde{X}_a \otimes \tilde{C}_a = \{\mu_{\tilde{X}_a}\mu_{\tilde{C}_a}, I_{\tilde{X}_a}I_{\tilde{C}_a}, v_{\tilde{X}_a} + v_{\tilde{C}_a} - v_{\tilde{X}_a}v_{\tilde{C}_a}\} \tag{7}$$

**Step 3.** Picture Fuzzy Sets with aggregation operators

Arithmetic Weighted of Picture Fuzzy (PFWA): The weights for $w = (w_1, w_2, \ldots, w_n)$ where $0 \leq w_j \leq 1$ and $\sum_{j=1}^{n} w_j = 1$:

$$\mathrm{PFWA}_w\left(\tilde{X}_1, \ldots, \tilde{X}_n\right) = \left\{1 - \prod_{j=1}^{n} \left(1 - \mu_{\tilde{X}_j}\right)^{w_j}, \prod_{j=1}^{n} I_{\tilde{X}_j}^{w_j}, \prod_{j=1}^{n} v_{\tilde{X}_j}^{w_j}\right\} \tag{8}$$

Geometric Weighted of Picture Fuzzy (PFWG):

$$\mathrm{PFWG}_w\left(\tilde{X}_1, \ldots, \tilde{X}_n\right) = \left\{\prod_{j=1}^{n} \mu_{\tilde{X}_j}^{w_j}, \prod_{j=1}^{n} I_{\tilde{X}_j}^{w_j}, 1 - \prod_{j=1}^{n} \left(1 - v_{\tilde{X}_j}\right)^{w_j}\right\} \tag{9}$$

**Step 4.** Score Functions

First score function:

$$SC1 = \mathrm{Score}_1\left(\tilde{X}_a\right) = \frac{1}{2}\left(1 + 2\mu_{\tilde{X}_a} - v_{\tilde{X}_a} - \frac{I_{\tilde{X}_a}}{2}\right) \tag{10}$$

Second score function:

$$SC2 = \mathrm{Score}_2\left(\tilde{X}_a\right) = \left(2\mu_{\tilde{X}_a} - v_{\tilde{X}_a} - \frac{I_{\tilde{X}_a}}{2}\right) \tag{11}$$

## 4 The Proposed Methodology

This study presents an innovative approach for selecting the most suitable COBOT types, whose use in supply chains has increased significantly in recent years due to the impact of digitalization, by evaluating them according to defined appropriate criteria. Pioneering the integration of SWARA and CODAS within a picture fuzzy framework offers a comprehensive methodology to tackle complex MCDM problems. The process started with a combination of alternatives and main and sub-criteria with expert opinions. The obtained weights are checked for consistency to make sure they appropriately reflect the criteria and sub-criteria's hierarchical structure. The PiF-SWARA framework of COBOT types provides a robust mechanism for prioritizing salient criteria in supply chains, thus facilitating a more accurate and reliable selection of AI technologies. Then, the PiF-CODAS method is used to evaluate and rank the alternatives according to their performance on the identified criteria. This improved PiF-CODAS framework provides a robust tool for evaluating COBOT types in digital supply chain processes under uncertain and complex decision-making conditions. The suggested PiF-SWARA-CODAS methodology's entire flowchart, which is displayed in Fig. 1, demonstrates its logical progression and usefulness.

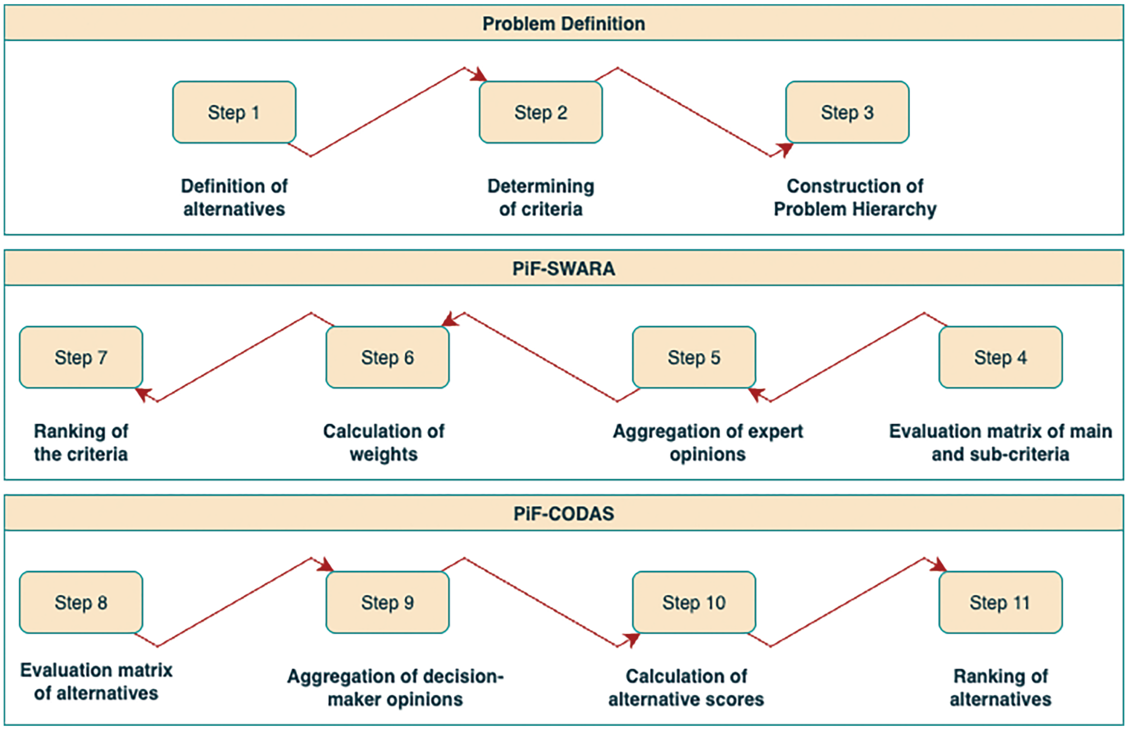


**Figure 1:** The flowchart of the proposed methodology

### *4.1 Picture Fuzzy SWARA*

The SWARA method, which was first presented in the literature by Keršuliene et al. [26], is a remarkable and inventive approach to data analysis and decision-making. The SWARA model is a widely used tool in many different fields; it is essential for estimating the subjective criteria weights or the degree of relevance of features. SWARA is a policy-based approach that uses priority-based weighting of criteria [28]. One of the most notable benefits of the SWARA method is that, unlike the AHP [29] and BWM [30] weighting methods, it requires a minimum number of processing steps and pairwise comparisons. This reduces computational requirements and increases the overall efficiency of the weighting process. The most important criterion is given the most priority in this process, while the least important criterion is placed at the bottom [27]. Additionally, the SWARA method was preferred over the Full Consistency Method (FUCOM) [31], Label-Based Weight Assessment (LBWA) [32], and Ordered Preference Approach (OPA) [33] methods. This is because while FUCOM and LBWA determine subjective weights, and OPA is used for objective weight assessments, these methods are generally more challenging when it comes to managing uncertainties in decision-making processes. In contrast, SWARA facilitates alignment with expert decisions through a simpler application. This method is used because it is more dependable than other decision-making procedures since it allows for more robust comparisons and requires fewer comparable data [34]. Furthermore, while the BWM and FUCOM methods require linear or nonlinear optimization, SWARA does not involve a modeling structure. This results in more straightforward and easily understandable calculations. This method stands out for its exceptional capacity to incorporate professional judgments regarding the significance of factors that are taken into account throughout the weighting process [26]. Despite all of this, the SWARA method has a significant disadvantage. The approach mostly depends on the decision-makers' subjective evaluations. The reliability and objectivity of the results may be impacted by bias and variability introduced into the weighting process by relying on expert opinion. Due to the method's subjective nature, the ability and reliability of those participating in the evaluation process have a significant impact on the accuracy of the results [35]. However, this situation may prevent a comprehensive assessment required in complex decision-making scenarios and hierarchical criteria structures. The results are analyzed by modifying the criterion weights through scenario analyses, and the risks that may arise from this disadvantage are evaluated. Researchers have been using this approach in a variety of fields in recent years. Ayyildiz and Erdogan [36] discussed how to choose parking lots for autonomous cars in cities that are seeing population development and rising car usage. Ataei et al. [37] assessed railway systems for sustainable transportation by employing weighting with interval rough numbers. Moslem et al. [38] evaluated the quality components of urban bus transport services using fuzzy Bonferroni and enhanced fuzzy SWARA To transition to a circular economy and reap its benefits, Saraji and Streimikiene [39] evaluated companies' production sectors in terms of circular supply chain management indicators with PiF-SWARA. Mishra et al. [40] presented the integrated SWARA-WASPAS technique for choosing bioenergy production. Ghoushchi et al. [41] prioritized solar panel system failures using information in conjunction with SWARA and GRA methodologies. To deal with uncertainties that may arise due to expert opinions in the decision-making process, this study integrated PiFs with SWARA. In practical decision-making, picture fuzzy numbers (PiFs) minimize information loss by offering a rich representation of fuzzy and uncertain data. Cuong and Kreinovich first proposed picture fuzzy sets in [23], which are a more sophisticated version of intuitionistic fuzzy sets (IFSs). By covering a wider range of responses, picture fuzzy sets improve on the capabilities of FSs, IFSs, and hesitant fuzzy sets and offer a more accurate and nuanced framework for handling challenging decision-making situations [26]. The crucial aspect of SWARA is that it relies on professional judgments to determine the relative significance of each criterion. The relevance weights of the criteria at each hierarchical level are determined in this study using the PiF-SWARA technique. The following steps are part of the PiF-SWARA methodology [35]:

**Step 1.** Using the language terms listed in Table 3, gather expert evaluations for each criterion to create an initial decision matrix.

**Step 2.** Create a picture fuzzy decision matrix by combining the expert assessments using the PFWA operator. This matrix will represent the diverse language inputs as picture fuzzy values.

**Step 3.** Determine the values of the crisp score.

**Step 4.** Sort the criteria according to their distinct score values in descending order.

**Step 5.** Compute the difference in score values between the current criterion ($j$) and the preceding one ($j-1$) to ascertain the comparative relevance of each criterion.

**Step 6.** Determine the comparison coefficient.

$$k_j = \begin{cases} 1, j = 1 \\ s_j + 1, j > 1 \end{cases} \tag{12}$$

**Step 7.** Calculate the estimated weights.

$$q_j = \begin{cases} 1, j = 1 \\ \dfrac{q_{(j-1)}}{k_j}, j > 1 \end{cases} \tag{13}$$

**Step 8.** Complete the criteria weights, making sure that the total number of criteria ($n$) is equal to the sum of the weights.

$$w_j = \frac{q_j}{\sum_{j=1}^{n} q_j} \tag{14}$$

**Table 3:** Linguistic terms for criteria

| Linguistic terms | PiFNs ($\boldsymbol{\mu}$, $\boldsymbol{I}$, $\boldsymbol{v}$) |
|---|---|
| RC—Remarkably considerable | (0.90, 0.05, 0.05) |
| EC—Exceptionally considerable | (0.75, 0.15, 0.10) |
| C—Considerable | (0.65, 0.30, 0.05) |
| A—Average | (0.30, 0.40, 0.30) |
| NC—Not considerable | (0.20, 0.30, 0.50) |
| N—Negligible | (0.00, 0.00, 1.00) |

### *4.2 Picture Fuzzy CODAS*

The CODAS method was developed by Ghorabaee et al. in 2016 [42]. Two metrics are used in the CODAS technique to evaluate alternative preferences. These are the Taxicab and Euclidean distances. It is a powerful and new method that evaluates alternatives based on their relative distance from the negative ideal solution (NIS). The Euclidean distance is the most basic and significant measurement. The distance between a taxi and the area of normal indifference is proportional. The optimal option is thought to be the one that deviates from the negative ideal solution the most. Taxicab distance is considered if the two options for decision-making cannot be compared in terms of Euclidean distance (equal or very close) [43]. Euclidean distance is particularly effective in distinguishing alternatives with significant differences in criterion performance. However, if the alternatives are similar or nearly equal, taxi distance is used as a secondary measure. Taxi distance is calculated by calculating the sum of the absolute differences between the criteria. The distances of alternatives to ideal solutions are processed more precisely because of the CODAS approach, which suggests a more reliable multi-distance measurement that considers the integration of Euclidean and taxi distances [44]. An efficient and modern approach for resolving MCDM issues is the CODAS method. It provides a very simple and methodical approach to representing uncertain real-life problems [45]. In the classic CODAS method, the distances under each criterion are directly summed without considering the effect of criterion weights. This is inconsistent with the actual situation. To counter this disadvantage, criterion weights are added and converted into fuzzy linguistic terms [46]. One of the reasons for choosing CODAS is that it is an innovative decision-making method that has emerged in recent years and has not yet been widely studied in the literature. There are some studies about the implementation of CODAS. Alkan [44] expanded the CODAS method to IVPFSs to rank renewable energy alternatives focused on sustainable development and use for Turkey under uncertainty. Kathirvel et al. [47] utilized the PiF-CODAS method to evaluate the alternatives defined for determining the location of a new vehicle dismantling facility in the Republic of Serbia. In this study, the CODAS method is extended to a Picture Fuzzy environment. This adaptation enhances the method's ability to handle uncertainty and ambiguity, making it suitable for evaluating COBOT alternatives, a significant technological innovation in supply chains. By utilizing PiFSs' extensive representation capabilities, the PiF-CODAS method offers a more thorough and precise framework for making decisions. The most important driving force behind the selection of the CODAS and SWARA methods is that they are recent methods that have emerged in recent years. The second driving force is that the results of such a study, which will guide the digital transformation in supply chains, have not yet been evaluated.

Below is a summary of the PiF-CODAS methodology's steps [40,45]:

**Step 1.** In order for decision makers (DMs) to evaluate the defined alternatives, PiFs are first evaluated against predefined criteria using the linguistic terms given in Table 4.

**Table 4:** Linguistic terms for alternatives

| Linguistic terms | PiFNs ($\boldsymbol{\mu}$, $\boldsymbol{I}$, $\boldsymbol{v}$) |
|---|---|
| VG—Very Good | (0.90, 0.01, 0.05) |
| G—Good | (0.75, 0.05, 0.15) |
| MG—Moderately Good | (0.60, 0.05, 0.30) |
| F—Fair | (0.50, 0.10, 0.40) |
| MB—Moderately Bad | (0.30, 0.05, 0.60) |
| B—Bad | (0.20, 0.05, 0.70) |
| VB—Very Bad | (0.10, 0.01, 0.80) |

**Step 2.** To ensure agreement and coherence, decision-makers' assessments are combined using the PFWA operator.

**Step 3.** For computational simplicity, PiFs are transformed into discrete scores using scoring functions.

**Step 4.** A weighted decision matrix is produced by applying criteria weights (derived from PiF-SWARA) to the total scores. The weight of the criteria is between 0 and 1.

$$b_{ij} = w_j X_{ij} \tag{15}$$

**Step 5.** The NIS is defined according to benefit or cost criteria.

In order to calculate benefit criteria;

$$ah_j = min_j \, b_{ij} \tag{16}$$

In order to calculate cost criteria;

$$ah_j = max_j \, b_{ij} \tag{17}$$

**Step 6.** For every choice, Euclidean distances are computed in relation to the NIS. Taxicab distances are used for differentiation when alternatives have close Euclidean distances.

$$E_i = \sqrt{\sum\nolimits_{j=1}^{n} \left(b_{ij} - ah_j\right)^2} \tag{18}$$

$$T_i = \sqrt{\sum\nolimits_{j=1}^{n} \left|b_{ij} - ah_j\right|} \tag{19}$$

**Step 7.** The matrix of relative assessment is produced.

$$Ra = \left[h_{ip}\right]_{n\times n} \tag{20}$$

$$h_{ip} = \left(E_i - E_p\right) + \left(\psi\left(E_i - E_p\right) \times \left(T_i - p\right)\right) \tag{21}$$

The total number of options is denoted by $n$. To ascertain whether the Euclidean distances between two options are sufficiently different, the function $\psi$ is employed as a threshold mechanism. It has the following definition.

$$\psi(y) = \begin{cases} 1 & \text{if } |y| \geq \tau \\ 0 & \text{if } |y| < \tau \end{cases} \tag{22}$$

In this case, decision-makers have selected $\tau$ as a threshold parameter. The Taxicab distance is used to further distinguish between two options if their absolute Euclidean distance differences are smaller than $\tau$.

**Step 8.** Each alternative's evaluation score is determined by adding up each of its relative evaluations for every criterion:

$$H_i = \sum\nolimits_{p=1}^{n} h_{ip} \tag{23}$$

**Step 9.** Lastly, the evaluation scores of the alternatives are used to rank them in descending order. The most advantageous choice is the one that receives the highest score.

## 5 Real Case Analysis

The selection of COBOT types is crucial for modern supply chain operations. Choosing the right type improves functionality on the production line. It facilitates safe and efficient human-robot collaboration and improves process quality. Choosing the wrong one risks both occupational safety and production performance. Alternatives specifying COBOT types were chosen through discussions with experts. Additionally, a thorough literature review was carried out, and consideration was given to the selection of contemporary technical systems. Managers can be directed toward a system that offers observable advantages by the alternatives that have been identified and their assessments based on these factors. Fig. 2 lists the options that were considered in this investigation.

The validity and reliability of the study must be established a team of experts who wish to comprehensively evaluate the defined alternatives. For this study, a team of four experts with extensive knowledge in the areas of digital transformations in the supply chain, production processes, and warehouse management was formed. These professionals are in charge of figuring out the fundamental assessment standards, evaluating their significance, and assessing different COBOT solutions. The specifics of these experts' information are displayed in Table 5 that follows.

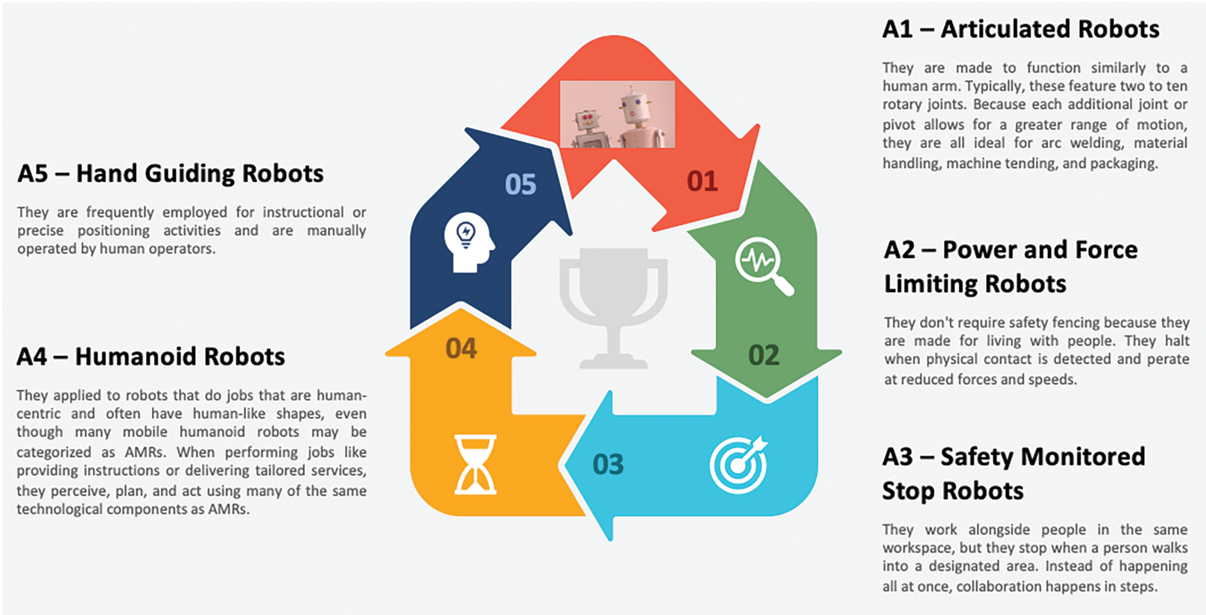


**Figure 2:** Proposed alternatives to COBOTs

**Table 5:** Decision makers' profiles

| DMs | Experience | Education | Job title | Area of expertise |
|---|---|---|---|---|
| DM1 | 5+ | BSc in Mechatronics Engineering | Project Management and Supply Chain Engineer | Supply Chain management and project management in the integrating of robots into production process |
| DM2 | 10+ | PhD in Production Management | Lecturer | Worked in production as a team leader in automotive industry. Production operations, lean processes are the current working area |
| DM3 | 10+ | PhD in Industrial Engineering | Associate Professor | Supply chain management, warehouse management, decision making |

(Continued)

**Table 5 (continued)**

| DMs | Experience | Education | Job title | Area of expertise |
|---|---|---|---|---|
| DM4 | 9 | PhD in Industrial Engineering | Associate Professor | Worked on a project in the digital transformation of production processes. Warehouse management, digital supply chain operations, decision-making |

### *5.1 Evaluating the Criteria Weights*

To evaluate alternative COBOT methods in more detail, a list of criteria was prepared based on a comprehensive literature review and in-depth interviews with industry experts. This evaluation approach emphasizes both the sustainability dimension and the importance of modern approaches in the digital supply chain for selecting the most important COBOT type. Table 6 presents the criteria used in this study.

**Table 6:** Criteria and references

| Criteria | References |
|---|---|
| C1. Cost | [2,12,19] |
| C2. Process quality | [12,19] |
| C3. Space utilization/Mobility situation | [12,14] |
| C4. Total speed | [48] |
| C5. Weight | [14,48] |
| C6. Power consumption | [9,48] |
| C7. Ergonomic conditions | [19] |
| C8. Eco-friendliness | [12] |
| C9. Pollution or waste flexibility | [49,50] |
| C10. Ability to adopt | [14,19] |
| C11. Cycle time | [19] |
| C12. Risk of injuries | [19] |

The relevance weights of each criterion for choosing the right COBOT type were established in this study using the PiF-SWARA approach. To compare the criteria thoroughly, an expert panel was assembled, and a number of the linguistic factors listed in Table 3 were employed. Table 7 displays the matrices that the experts produced.

Four DMs measure the relative importance of five different types of COBOTS using the linguistic terms given in Table 3. To ensure the validity and reliability of the study's results, each expert's weight is equally adopted, taking into account their experience. Table 7 shows the quantitative evaluation of the criteria determined by the experts using linguistic variables. Subsequently, a collective decision matrix is created using Eqs. (8) and (9). Table 8 states the result of aggregating the experts' linguistic evaluations using PFWA operator.

**Table 7:** Quantification of criteria

| Criteria | DM1 | DM2 | DM3 | DM4 |
|---|---|---|---|---|
| C1 | RC | EC | RC | EC |
| C2 | EC | EC | RC | EC |
| C3 | EC | RC | C | A |
| C4 | A | A | C | RC |
| C5 | NC | NC | NC | NC |
| C6 | A | N | EC | A |
| C7 | NC | NC | A | RC |
| C8 | NC | A | NC | NC |
| C9 | NC | C | NC | NC |
| C10 | RC | RC | A | NC |
| C11 | C | A | EC | C |
| C12 | NC | NC | NC | C |

**Table 8:** Aggregating the four experts' linguistic evaluations

| Criteria | $\mu$ | $I$ | $v$ | Score values |
|---|---|---|---|---|
| C1 | 0.8419 | 0.1014 | 0.0753 | 0.8326 |
| C2 | 0.8012 | 0.1260 | 0.0878 | 0.7937 |
| C3 | 0.7202 | 0.2369 | 0.1316 | 0.6759 |
| C4 | 0.6381 | 0.3005 | 0.1845 | 0.5765 |
| C5 | 0.2000 | 0.3000 | 0.5000 | 0.2000 |
| C6 | 0.4084 | 0.2562 | 1.0000 | 0.0761 |
| C7 | 0.5399 | 0.2730 | 0.3615 | 0.4527 |
| C8 | 0.2263 | 0.3265 | 0.4561 | 0.2218 |
| C9 | 0.3494 | 0.3000 | 0.4130 | 0.3182 |
| C10 | 0.7264 | 0.2154 | 0.2503 | 0.6304 |
| C11 | 0.6174 | 0.2930 | 0.1316 | 0.5964 |
| C12 | 0.3494 | 0.3000 | 0.4130 | 0.3182 |

In the next step, the sharp values of the fuzzy numbers are obtained using Eqs. (10) and (11) and then ranked from most important to least important. Subsequently, the relative importance of the criteria ($H_j$) and the comparison coefficient ($k_j$) are calculated using Eq. (12). Then, the initial weight ($q_j$) of each criterion is calculated using Eq. (13). Finally, the final weight ($\omega_i$) of the criteria is obtained using Eq. (14). All the results obtained are presented in Table 9. As a result of the analysis, "Cost" was determined to be the most important criterion with a weight of 0.1145. This is followed by "Process quality” and “Space utilization/mobility situation” with weights of 0.1102 and 0.0986, respectively. On the other hand, the “Power consumption” criterion was determined to be the least important criterion with a weight of 0.0557. The results reveal that businesses prioritize economic sustainability and production flexibility when selecting COBOTs. However, energy consumption appears to be a secondary priority compared to other criteria.

**Table 9:** Results of PiF-SWARA

| Criteria | Crisp value ($S_j$) | Relative importance of the criteria ($H_j$) | Comparative coefficient ($k_j$) | Initial weight of each criterion ($q_j$) | Criteria weight ($w_j$) |
|---|---|---|---|---|---|
| C1 | 0.8326 | – | 1.0000 | 1.0000 | 0.1145 |
| C2 | 0.7937 | 0.0389 | 1.0389 | 0.9626 | 0.1102 |
| C3 | 0.6759 | 0.1178 | 1.1178 | 0.8611 | 0.0986 |
| C10 | 0.6304 | 0.0455 | 1.0455 | 0.8236 | 0.0943 |
| C11 | 0.5964 | 0.0340 | 1.0340 | 0.7966 | 0.0912 |
| C4 | 0.5765 | 0.0198 | 1.0198 | 0.7811 | 0.0894 |
| C7 | 0.4527 | 0.1238 | 1.1238 | 0.6950 | 0.0795 |
| C9 | 0.3182 | 0.1345 | 1.1345 | 0.6126 | 0.0701 |
| C12 | 0.3182 | 0.0000 | 1.0000 | 0.6126 | 0.0701 |
| C8 | 0.2218 | 0.0964 | 1.0964 | 0.5588 | 0.0640 |
| C5 | 0.2000 | 0.0218 | 1.0218 | 0.5468 | 0.0626 |
| C6 | 0.0761 | 0.1239 | 1.1239 | 0.4865 | 0.0557 |

### *5.2 Calculating the Alternatives*

In the second stage, after calculating the weights of the criteria using PiF-SWARA, the COBOT types were ranked using the PiF-CODAS method with the weights obtained in the first stage. The expert team quantitatively calculated the five types using the linguistic variables and corresponding picture fuzzy numbers in Table 10.

**Table 10:** Matrix of aggregated alternative evaluations

| | A1 | | | A2 | | | A3 | | | A4 | | | A5 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\mu$ | $I$ | $v$ | $\mu$ | $I$ | $v$ | $\mu$ | $I$ | $v$ | $\mu$ | $I$ | $v$ | $\mu$ | $I$ | $v$ |
| **C1** | 0.822 | 0.022 | 0.103 | 0.666 | 0.059 | 0.228 | 0.553 | 0.071 | 0.346 | 0.842 | 0.022 | 0.087 | 0.602 | 0.071 | 0.291 |
| **C2** | 0.776 | 0.033 | 0.136 | 0.734 | 0.040 | 0.173 | 0.684 | 0.047 | 0.221 | 0.644 | 0.050 | 0.252 | 0.567 | 0.059 | 0.322 |
| **C3** | 0.726 | 0.022 | 0.180 | 0.734 | 0.033 | 0.168 | 0.666 | 0.059 | 0.228 | 0.764 | 0.040 | 0.146 | 0.801 | 0.033 | 0.114 |
| **C4** | 0.749 | 0.027 | 0.163 | 0.438 | 0.084 | 0.460 | 0.408 | 0.071 | 0.490 | 0.391 | 0.050 | 0.505 | 0.567 | 0.050 | 0.312 |
| **C5** | 0.667 | 0.033 | 0.228 | 0.356 | 0.059 | 0.542 | 0.503 | 0.059 | 0.383 | 0.624 | 0.047 | 0.274 | 0.514 | 0.050 | 0.371 |
| **C6** | 0.543 | 0.071 | 0.346 | 0.553 | 0.071 | 0.346 | 0.580 | 0.084 | 0.313 | 0.644 | 0.040 | 0.255 | 0.500 | 0.100 | 0.400 |
| **C7** | 0.527 | 0.071 | 0.360 | 0.812 | 0.027 | 0.111 | 0.719 | 0.050 | 0.178 | 0.734 | 0.040 | 0.173 | 0.842 | 0.022 | 0.087 |
| **C8** | 0.591 | 0.050 | 0.300 | 0.719 | 0.047 | 0.186 | 0.717 | 0.033 | 0.192 | 0.734 | 0.040 | 0.173 | 0.743 | 0.033 | 0.161 |

(Continued)

**Table 10 (continued)**

| | A1 | | | A2 | | | A3 | | | A4 | | | A5 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\mu$ | $I$ | $v$ | $\mu$ | $I$ | $v$ | $\mu$ | $I$ | $v$ | $\mu$ | $I$ | $v$ | $\mu$ | $I$ | $v$ |
| **C9** | 0.468 | 0.071 | 0.428 | 0.602 | 0.071 | 0.291 | 0.567 | 0.059 | 0.322 | 0.602 | 0.071 | 0.291 | 0.553 | 0.059 | 0.335 |
| **C10** | 0.567 | 0.059 | 0.322 | 0.822 | 0.022 | 0.103 | 0.684 | 0.050 | 0.212 | 0.567 | 0.059 | 0.322 | 0.776 | 0.033 | 0.136 |
| **C11** | 0.656 | 0.033 | 0.237 | 0.540 | 0.050 | 0.357 | 0.717 | 0.033 | 0.192 | 0.624 | 0.050 | 0.262 | 0.440 | 0.059 | 0.456 |
| **C12** | 0.664 | 0.033 | 0.237 | 0.623 | 0.015 | 0.263 | 0.482 | 0.033 | 0.398 | 0.624 | 0.050 | 0.262 | 0.497 | 0.050 | 0.385 |

The assessments of each expert are used to generate a weighted choice matrix. For every criterion, a negative ideal solution is identified within the weighted matrix. The primary and secondary distances from the negative ideal solution are then computed with Eqs. (15)–(19), as indicated in Table 11.

**Table 11:** The euclidean and taxicab distances from the NIS

| | A1 | A2 | A3 | A4 | A5 |
|---|---|---|---|---|---|
| **Euclidean** | 0.088 | 0.066 | 0.056 | 0.074 | 0.062 |
| **Taxicab** | 0.469 | 0.437 | 0.376 | 0.455 | 0.399 |

The DM can modify the threshold parameter, $\tau$, which is employed in the computations. Setting this option to a value between 0.01 and 0.05 is advised. Similar to Ghorabaee et al. [42], we employed the value $\tau = 0.02$ in this study's computations. The final ranking and the associated scores are shown in Table 12 with Eqs. (20)–(23). The alternatives are then ordered based on their scores.

**Table 12:** Results of PiF-CODAS

| Alternative | Score | Ranking |
|---|---|---|
| A1. Articulated robots | 0.29002 | 1 |
| A2. Power and Force limiting robots | −0.0452 | 3 |
| A3. Safety monitored stop robots | −0.1608 | 5 |
| A4. Humanoid robots | 0.02358 | 2 |
| A5. Hand guiding robots | −0.1076 | 4 |

According to the final results, Articulated Robots (A1) ranked highest, being the most highly evaluated alternative. Humanoid Robots (A4) follow, due to their widespread use. Power and Force Limiting Robots (A2) ranked third, and despite their significant advantages, they fell slightly behind A1 and A4 due to their low payload and limited agility. Hand Guiding Robots (A5) and Safety Monitored Stop Robots (A3) ranked lower, indicating their limitations due to their lower efficiency and limited application areas. Overall, the results indicate that articulated robots, which provide flexibility, cost-effectiveness, and process efficiency, are the most suitable option for the industry. Hand Guiding Robots, which ranked last, received lower priority than other alternatives due to their simple structure and limited functionality.

### *5.3 Validation of Expert Weights*

In the analysis conducted to validate the expert weights, the decision-making weights were altered to observe scenarios under different conditions. In the first scenario (S0), equal weights (0.25 each) were assigned to all experts, as applied in the study's results. Four different scenarios were tested to evaluate the robustness of the results; here, one expert was assigned a dominant weight of 0.85 (for instance, in S1: $w_1 = 0.85$, $w_2 = 0.05$, $w_3 = 0.05$, $w_4 = 0.05$), while the remaining three experts shared the remaining weight equally (0.05 each). Table 13 shows the scores obtained by the alternatives in the calculations made after changing the expert weights.

**Table 13:** Alternative scores for different expert weights

| Alternative | S0 | S1 | S2 | S3 | S4 |
|---|---|---|---|---|---|
| A1. Articulated robots | 0.29002 | 0.23567 | 0.14700 | 0.36382 | 0.31886 |
| A2. Power and Force limiting robots | −0.0452 | −0.0034 | 0.00986 | −0.08482 | −0.0606 |
| A3. Safety monitored stop robots | −0.1608 | −0.1521 | −0.15432 | −0.15999 | −0.1738 |
| A4. Humanoid robots | 0.02358 | 0.02736 | 0.01889 | 0.03372 | 0.00761 |
| A5. Hand guiding robots | −0.1076 | −0.1075 | −0.02143 | −0.15275 | −0.0921 |

Although one expert has a dominant weight in all scenarios, the ranking of alternatives has not changed. The results of the study actually prove the suitability of assigning equal weights (0.25) to all decision makers, as in S0, for the validation of the results. The findings show that the suggested method provides consistent results in a variety of expert influence situations. However, it should be mentioned that fuzzy MCDM techniques are mostly based on subjective assessments, which could lead to uncertainty or inconsistent results.

### *5.4 Sensitivity Analysis*

This study examines how the prioritization of COBOT types, now an integral part of digital supply chains, may change under evolving strategic approaches and supply chain dynamics, using scenario-based analysis. By methodically modifying the weights given to evaluation criteria, scenario analysis makes it possible to assess alternative projects under various priorities. The findings of the sensitivity analysis show that the suggested strategy adapts well to changing situations and produces results that are in line with adjustments to the weights of the criterion [48]. This method improves the MCDM results' robustness and practical applicability while also reflecting the intricacies of the real world. The first scenario, defined as S0, represents the original results of the study. In scenario S1, the weights of the criteria with the highest weight and the criteria with the lowest weight have been swapped. In scenario S2, the highest criterion weight and the second lowest criterion weight have been changed. In the third scenario, the alternatives have been ranked by changing the highest weight and the third lowest weight. In the fourth and fifth scenarios, the highest weight and the fourth and fifth lowest weights have been changed, and the alternatives have been ranked with the new weights obtained.

A comparison summary of alternate rankings for each scenario (S0–S5) is shown in Fig. 3. Scenarios S1 through S5 show results under various fictitious stakeholder priorities and policy perspectives. At the same time, S0 displays the baseline results generated by our suggested model utilizing the original expert-derived criterion weights. As can be seen from Fig. 3, the most important and least important alternatives have remained unchanged in the scenario analyses. This provides us with an important inference regarding the robustness of the results.

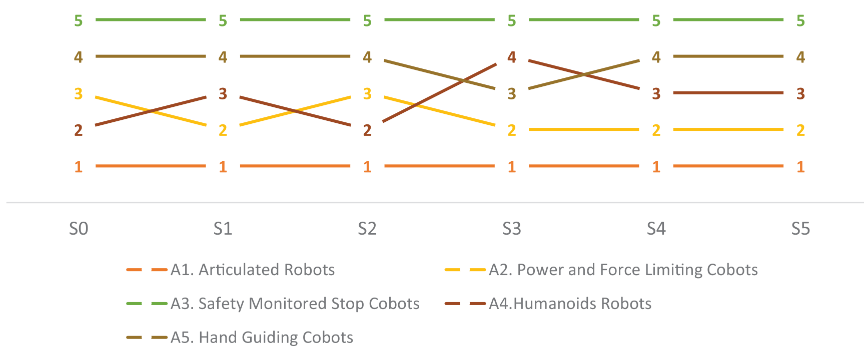


**Figure 3:** Alternative rankings according to scenarios

## 6 Discussion

Digitalization in supply chains is achieved through the increased use of automated systems in processes. In recent years, robots that can work safely, flexibly, and efficiently alongside humans have begun to be widely used in modern production processes. This has paved the way for the digital transformation of smart factories through the use of sensors, human-centered production, collaboration with IoT, and big data. These machines, defined as COBOTs, enable human-robot collaboration. They have begun to be discussed more frequently with I5.0. Production processes are being improved by taking advantage of both human flexibility and robot speed and accuracy. In 2016, the International Organization for Standardization (ISO) developed the ISO/TS 15066:2016 Robots and robotic devices—COBOTs standard, establishing a technical specification that enables humans and industrial robots to work together and ensures safety requirements are met. As part of this study, the types of COBOTs included in the relevant standard [6] were reviewed, and an in-depth review of the literature was conducted. According to the evaluation made by the experts among the alternative robot applications defined, the most important and priority one was A1. Articulated Robots. The movements of articulated robots are intended to mimic those of a human arm. Articulated robots work at high speeds and with high precision, performing movements similar to those of the human arm in heavy-duty tasks. These robots, which are particularly popular in the automotive industry along production lines, work separately from humans behind safety fences. Typically, these feature two to ten rotary joints. Because each additional joint or pivot allows for a greater range of motion, they are all ideal for arc welding, material handling, machine tending, and packaging [8]. Because articulated robots can precisely perform carrying jobs under various motion patterns, they can satisfy real industrial needs [49]. Instead of robots that work with more people and are flexible, this type of robot, which works at high speeds, with heavy loads, and difficult dimensions, fully integrated with automatic systems, has been considered the most important. It has been determined that operations performed using an articulated robot application with a flexible automation system are six times faster than those performed manually using traditional methods [51]. This is an important example of why this application is so widely preferred. On the other hand, the implementation of smart factories requires articulated robots with adaptable automation systems, but small and medium-sized businesses find it challenging due to their high initial investment costs [50]. The second most important type of robot is the A4. Humanoid Robots. These robots, which can interact with humans, are slower and have a lower load capacity. These robots, which are preferred in experimental processes and high-risk environments in R&D operations, can perform various functions that we do not want humans to perform. Humanoid robots are highly flexible and have a tiny support base; hydraulic humanoid robots have additional benefits like high power output and density [52]. Adult-sized humanoid robots, usually taller than one meter and able to walk on two feet, have many different features, such as sophisticated control systems, sophisticated planning, complex mechatronics, extensive AI sensing, maximum mobility and working range, and improved human-robot interaction [53]. To set up human time for more creative pursuits, autonomous robots are expected to take over duties that humans are compelled to undertake in hazardous situations, in hostile locations, and in low-value jobs that fixed or palletized robots cannot complete [54]. On the other hand, it should not be forgotten that humanoid robots have become more widespread in recent years and are used more in R&D projects. According to the results obtained, A2. Power and Force Limiting Robots ranked third. These robots, which are one of the COBOT types listed in ISO/TS 15066, can be used in environments where humans work with low load capacity and speed. They are designed to work alongside the operator by utilizing a new type of robotic system called cooperation. Safety measures like barriers or other optical devices are typically not necessary because the concept involves a specific operation. Because of its sophisticated sensor systems, this robotic arm can "sense" the over-acting forces while it is in use. When it detects an excess of energy, pressure, or power, it is set to shut off [55]. According to the results of the study, A.5 Hand Guiding Robots rank fourth, while A3. Safety Monitored Stop Robots rank fifth. The fact that these types of robots, which involve a high degree of human-robot interaction, are not used in mass production conditions has made them less desirable. It is a fact that robots that perform mass production at high speeds and with full automation in supply chains will yield more effective results in terms of process efficiency. Being rated as the lowest does not actually indicate that Safety Monitored Stop Robots are insignificant. It only indicates that they are the least prioritized among other alternatives, according to expert opinions.

## 7 Conclusion and Future Directions

In recent years, due to increasing competitive conditions, issues such as improving efficiency and reducing costs in all processes within supply chains have become extremely important. With the emergence of I5.0, one of the most important functions of human-machine collaboration, which has been increasingly researched, is the use of COBOTs in processes. This study presents an MCDM model that considers the selection of COBOT types, a technology of great importance based on human-machine collaboration. With this model, criteria that enable the proper evaluation of COBOT types were first identified. During the determination of evaluation criteria, the literature was thoroughly researched, and expert opinions were utilized. The PiF-SWARA approach was adopted to determine the importance levels of the criteria, and picture fuzzy sets were used to model uncertainties in the decision-making process. The analysis revealed that the most important criterion was "C1. Cost" and the least important criterion was "C12. Power consumption." Under competitive conditions, it is important for factories to make the right investments to ensure efficiency and cost reduction as quickly as possible. Investing in the right equipment affects both initial costs and long-term expenses. Therefore, strategic investment decisions that provide sustainability and competitive advantage have come to the fore. The fact that power consumption is considered the least important criterion stems from businesses viewing energy costs as a secondary priority compared to other factors in their decision-making processes. Criteria such as investment cost, process quality, speed, or ergonomics directly affect production efficiency, work safety, and the return on investment period, while energy consumption has a relatively longer-term and indirect effect. This has resulted in it being ranked last among the criteria. After determining the criterion weights, COBOT types were ranked using the PiF-CODAS method. "A1. Articulated Robots" emerged as the most suitable COBOT alternative based on the criteria identified. Articulated robots have high mobility thanks to joints with multiple axes of rotation similar to the human arm. They are preferred for their flexible and precise performance in a wide range of production tasks such as welding, assembly, painting, and material handling. It has a direct positive impact on process quality (C2), overall speed (C4), and cycle time (C11). It also offers advantages in terms of space utilization/mobility (C3) due to its ability to easily adapt to various production lines. With a high level of automation, they reduce human error, providing critical benefits in terms of workplace safety and injury risk (C12). Although the initial investment cost (C1) may be high in some cases, the resulting increase in productivity and quality improvements accelerates the return on investment. The final alternative evaluated was "A3. Safety Monitored Stop Robots." This robot type received a lower score than others in the evaluation conducted by experts based on the criteria. Being focused exclusively on safety has made these robots less important. Although safety is an important factor, they have been seen as a less desirable option because they lag in terms of process quality, productivity, and flexibility.

A scenario analysis was conducted to test the robustness and validity of the results obtained in the study. The robustness of the prioritization results was tested under different strategic perspectives. First, a validation analysis was performed to evaluate the results related to differences among experts by changing their weights. Although the expert weights were implemented to give a high weight to an expert in each scenario, it was observed that the alternative rankings did not change in the results. Then, by changing the criterion weights, the attitudes of the alternatives in different scenarios were examined with sensitivity analysis. It was observed that the alternative rankings remained the same despite changes in the weight distributions. The sensitivity analysis also revealed that the most important and least important alternatives did not change, while there were some differences in the relative rankings of the other alternatives. The results obtained from the sensitivity analysis support the consistency and robustness of the study. The results obtained actually demonstrate the importance that the industry attaches to robotic processes operating under conditions of high efficiency and mass production. This study has provided participants from academia and the manufacturing industry with different insights into the continuous development and prioritization of COBOTs in human-robot environments.

Future research could involve comparing other MCDM techniques, recalculating the suggested methodology under various fuzzy set extensions, assessing the outcomes, and determining how robust it is. Additionally, IoT-based monitoring and digital twin systems can be incorporated to enable COBOTS to be dynamically reprioritized as production demands and working conditions change. The study can be expanded to include installation, maintenance, training, and end-of-life issues, enabling long-term cost-effectiveness and performance tracking. Applications across different industries can be tested. This way, the strategic value of COBOT selection as a driving force for efficiency, adaptability, and sustainability in next-generation supply chains can be enhanced in the future.

There are some limitations to this study. It would be useful to evaluate the results obtained by consulting more experts and comparing the results with existing studies. Adding more diverse criteria and applying them in different sectors would help to produce more generalizable results. There should be new research lacking validation against a real-world decision outcome.

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