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EVALUATION OF THE TRANSITIONS POTENTIAL TO CYBER-PHYSICAL PRODUCTION SYSTEM OF HEAVY INDUSTRIES IN TURKEY WITH A NOVEL DECISION-MAKING APPROACH BASED ON BONFERRONI FUNCTION

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ABSTRACT

Purpose: This study examines the potential of production systems of the heavy industry branches with the help of cyber-physical systems. Sources of public and private sectors may not be sufficient to transform and develop all heavy industry branches simultaneously. Because of that, policymakers can determine priority industries for development and growth, which are sustainable and balanced in a country.

Methodology: In current study, the proposed approach uses the LMAW (Logarithm Methodology of Additive Weights) technique to identify priority sectors. The LMAW is a novel MCDM (Multi-Criteria Decision Making) technique providing an opportunity to evaluate both objective and subjective criteria; in addition, it uses the Bonferroni functions to transform the subjective evaluations of decision-makers to the group decision.

Findings: It has been observed that the most significant criterion is overall equipment effectiveness (OEE), and the most prior branch of heavy industry is the aerospace industry.

Originality: This paper examines the transformation process of the heavy industry branches to the cyber-physical systems by using a new MCDM approach.

Keywords: Heavy Industries, LMAW, Bonferroni Function, Multicriteria Group Decision-Making, Cyber-Physical Systems.

JEL Codes: D2, C44, D81, E23.

TÜRKİYE'DE AĞIR SANAYİ ENDÜSTRİLERİNİN SİBER-FİZİKSEL ÜRETİM SİSTEMLERİNE GEÇİŞ POTANSİYELLERİNİN YENİ BİR BONFERRONİ FONKSİYONU TEMELLİ KARAR VERME YAKLAŞIMI ILE DEĞERLENDİRİLMESİ

ÖZET

Amaç: Bu çalışma ağır sanayi alt sektörlerinin üretim sistemlerinin siber-fiziksel sistemler yardımıyla dönüştürebilme potansiyellerini incelemektedir. Birçok ülkede kamu ve özel sektör kaynakları, bütün ağır sanayi endüstrilerinin eş zamanlı olarak geliştirilmesi ve dönüştürülmesi için yeterli olamayabilmektedir. Bu nedenle politika yapıcılar dengeli ve sürdürülebilir bir gelişim ve kalkınma yaratabilmek için öncelikli sektörler belirleyebilirler.

Yöntem: Mevcut çalışmada önerilen yaklaşım, öncelikli sektörlerin belirlenmesi için LMAW (Logarithm Methodology of Additive Weights) tekniğinden yararlanmaktadır. LMAW tekniği hem nicel hem de nitel kriterlerin birlikte değerlendirilmesine imkân tanıyan aynı zamanda karar vericilerin öznel değerlendirmelerinin grup kararına dönüştürülmesinde Bonferroni fonksiyonunu temel alan çok kriterli karar verme (ÇKKV) yaklaşımlarından birisidir.

Bulgular: LMAW tekniğinin uygulanması sonucunda çalışmada en etkili değerlendirme kriterinin genel ekipman verimliliği olduğu ve ilk sırada Havacılık ve Uzay Sanayi Endüstrisinin yer aldığı gözlemlenmiştir.

Özgünlük: Bu çalışma ağır sanayi alt sektörlerinin siber fiziksel sistemlere geçiş sürecini yeni bir ÇKKV yaklaşımı kullanılarak incelemektedir.

Anahtar Kelimeler: Ağır Sanayi, LMAW, Bonferroni Fonksiyonu, Çok Kriterli Grup Karar Verme, Siber-Fiziksel Sistemler.

JEL Kodları: D2, C44, D81, E23.

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1. INTRODUCTION

Heavy industry is a field of business with highly complicated production and supply chain processes, which requires high investment costs and heavy machines, equipment, and extensive facilities to make production. The heavy industry includes aerospace, shipbuilding, mining, machine tool building, locomotive manufacturing, oil and gas, steel production, chemical production, and large buildings and infrastructure (CFI, 2021). Also, heavy industry is an upstream industry, which means that high energy consumption is a significant feature of the heavy industry (Lin and Liu, 2016). Hence, large-scale private companies or public institutes mostly conduct these activities due to high investment and operational costs. Heavy industrial enterprises are primarily companies, which are active at a high capacity. In addition, their target customers are different industries or public authorities instead of a broad consumer mass consisting of individuals and small enterprises. For instance, a company active in aerospace and manufactures commercial planes does not expect to take orders from all individuals.

From this perspective, heavy industrial enterprises have high investment and operational risks. On the other hand, they provide contributions to the development and growth of countries on a vast scale. Therefore, successfully installing and operating these industries depends on detailed planning processes, which carry out from a rational perspective. In addition, Industry 4.0, we are in, has started to suppress the heavy industrial enterprises and all other industries and businesses for keeping pace with this most incredible transformation process. As a condition for surviving in the highly competitive and struggling business environment, it is crucial to carry out business activities with the highest quality and logistics speed and lowest operational costs. Hence, using instruments, which can technologically develop production, supplying, and logistics processes may be a good solution for heavy industries to keep pace with the requirements of the industry 4.0 process. As a result, companies have become necessary to redesign their operations and processes as proper to the requirements of the Industry 4.0 process, whether small or large-scale enterprises.

This situation is forced to the heavy industries on a vast scale when the structural problems are considered. Being low flexibility of these companies may cause to increase the existing risks much more. In addition to the risks, digital transformation is more complicated and costlier for heavy industrial enterprises than more flexible small and medium-sized enterprises. When it is evaluated from this perspective, planning and managing the synchronously digital transformation for all branches of heavy industry is extremely difficult and costly. Moreover, designing the digital transformation and technological development process for all branches of heavy industry is not practical for policymakers of countries; it may also cause public source usage improperly and unproductively. Therefore, decision-makers should focus on priority areas, which provide higher added value and can be conducted of this transformation with lower costs and efforts to transform these branches from a more realistic and applicable perspective. In addition, focusing on these kinds of priority areas of the heavy industry may be essential for designing sustainable and manageable transformation processes.

When considered from this point of view, one of the main components of Industry 4.0 is the Cyber-Physical Systems CPSs (Makris et al., 2019), and it requires to use of automation and autonomous systems in production processes at the maximal level. Already, CPS is motivating many research agendas related to production systems around the world (Riberio, 2017), and CPSs, which are a crucial part of the 4th Industrial Revolution (4IR), have started to transform the production system CPSs. CPSs provide connections among all production parties (Daflon et al., 2021) such as machines, humans, equipment, and others with the help of technological instruments (i.e., cloud systems, internet of things, RFID applications, and sensors). Besides, these systems can help produce routine and standardized behaviors for the elements of the production systems by developing algorithms. Also, CPS can provide opportunities for interaction and integration between the physical world and the digital world (Iansiti and Lakhani, 2014). As a result, they can help solve many problems encountered in actual production processes by transferring from the real world to the virtual environment (Gaggioli, 2018) with the help of the simulation technique. As a natural result, depending on reducing the usage of human resources in production processes, human errors are also reduced (Ali and Hong, 2018), and production processes become more speedy, effective, and productive (Pascual et al., 2021). Creating this kind of system is extremely difficult for heavy industries having relatively low flexibility. However, being managerial abilities and high financial powers can be accepted as advantages of heavy industrial enterprises.

Automation processes in smart factories mean regular, planned, and organized interactions (Lu et al., 2020) among machines, devices, and humans to organize the production processes. For instance, if any problem on source utilization in any production phase happens, it means giving orders for this requirement automatically and autonomously to the suppliers without a decision-making process. Therefore, CPS can help solve any problem, i.e., unexpected malfunction of machines and equipment, lack of resources such as human force, raw materials, semi-finished products, etc. Thus, production and logistics systems can be run in full capacity and unproblematic based on the successful integration of CPSs.

However, implementation steps and ways followed by all companies and industries for digital transformation are not sufficiently precise (Shahi and Sinha, 2020; Zaoui and Souissi, 2020), and obtaining crisp values for related data may be difficult and even impossible. This situation may source from data publishing habits of companies and being insufficient of the developed methodologies for obtaining the crisp values, or they have not existed. Hence, it has not developed a commonly held measurement system for identifying the crisp values for alternatives concerning criteria even though there are some well-meaning attempts, as Industry 4.0 is a pretty new process. From this perspective, there are severe and notable gaps in the existing literature on production systems, in addition to all processes of industry 4.0.

When the literature is reviewed comprehensively, the central part of the previous work existing in the literature examined CPSs, or they dealt with the implementation of CPSs in production companies and industries with a general view. From this perspective, these papers did not forward an idea that can CPSs be more effective in which industry(s) and made general evaluations on applying these systems for all industries only. However, each industry has different dynamics and specific characteristics; hence, the digital transformation process requires different scenarios for each industry. More importantly, each industry has a different potential for success related to CPSs. When they are evaluated from this perspective, there are severe gaps in the literature in the aspect of studies examining the potential of success of the industries on the implementation of CPSs. In addition, according to the authors' information, there is no paper evaluating the digital transformation process of the heavy industries concerning CPSs in the existing literature. By keeping in mind these gaps and requirements, the current paper examines the potential of the heavy industries related to the CPSs. Also, it tries to show priority branches of heavy industry that can be allocated sources and made investment for the digital transformation process by public and private sectors, as the sources of the public and private sectors are not limitless. Also, the proposed approach in the current paper has valuable contributions with respect to theoretical as summarised below to the existing literature.

The current paper proposes a novel, applicable and powerful MCDM (Multi-Criteria Decision Making) approach, keeping in mind these gaps in the existing literature and requirements of the practitioners and decision-makers in related branches of heavy industries. The proposed approach was introduced firstly by Pamucar et al. (2021), and it is a novel MCDM framework presenting a new algorithm different from other traditional and popular MCDM approaches. It has many relative advantages compared to the other popular MCDM techniques.

First, it is maximally consistent and stable and can not be affected by the rank reversal problem; hence, the ranking results do not change dramatically when we add or remove a criterion or decision alternatives. Because of that, the (-Logarithm Methodology of Additive Weights (LMAW) approach is more reliable in a dynamic environment than others for decision-makers. Also, the most significant contribution of the LMAW technique is to give better, accurate and reliable results, as it is a maximally consistent and stable MCDM framework (Pamucar et al., 2021). This methodological implication of the technique has been approved in the current paper to solve the decision-making problem on heavy industry branch selection for applying the CPS.

The proposed approach's mathematical framework and basic algorithm do not change based on the number of criteria and decision alternatives; it also allows both objective and subjective criteria. In addition, it does not require a different technique for identifying the weights of criteria. Hence, this approach can determine the criteria weights. Also, it uses the Bonferroni function for aggregating the subjective evaluations of the decision-makers. It provides a flexible decision-making environment to the decision-makers (Pamucar et al., 2021).

The motivations for the study are as follows. First, this paper introduces an applicable, robust, and effective MCDM framework to provide a powerful and flexible evaluation tool to the practitioners and decision-makers. The proposed mathematical tool can help make evaluations better for relating to selecting the branch of heavy industries, which are planned to transform their production systems into CPPSs. Hence, it can provide an opportunity to apply public incentives and subsidies and support the right and appropriate industrial fields. Thus, more efficient use of resources of public and private sectors may be possible.

Second, we decided to use the LMAW technique, as it provides reliable, realistic, and reasonable results because it is a maximally consistent and stable approach and is resistant to the rank reversal problem. In addition to these advantages, it has a very easily followable basic algorithm, and decision-makers can apply it without advanced mathematical information. Based on its advantages, it can help to fill the gaps related to the requirement of a methodological frame to solve these kinds of decision-making problems.

Third, contrary to research that have studied this topic from a general perspective, this paper examines the branches of the heavy industry from a more detailed perspective. Therefore, we considered the significant differences and dynamics among different branches of heavy industry to identify the best heavy industry branch having the potential to gain success for transforming its production system to an advanced and technologically improved production system. From this perspective, it can help determine a road map for digital transformation for the industries in a country.

In addition, we sought reasonable and realistic answers to the research questions. The research questions were determined by researchers as follows. i) is it possible to apply a mathematical model or decision support system to identify the priority branch of heavy industry to implement incentives, subsidies, and supports for digital transformation. ii) Are decision-makers in these industries make decisions based on their experiences and individual judgments only? iii) what are the significant criteria to identify the appropriate heavy industry branch?

The rest of the paper is organized as follows. In section 2, the proposed LMAW technique and its basic algorithm are demonstrated in detail. In section 3, the suggested approach has been implemented to evaluate the branches of the heavy industry concerning the suitability of digital transformation by using the CPS in their production processes. Also, a comprehensive sensitivity analysis was performed to test the validity of the proposed MCDM framework. In section 4, the overall results are evaluated and discussed. In addition, the methodological and managerial implications of the proposed approach and the current paper are indicated in this section. In section 5, the current paper is concluded; besides, limitations of the paper and recommendations to authors who conduct future works on this issue are indicated.

2. LITERATURE REVIEW

In this section, we review the existing literature in detail. We noticed severe and surprising gaps in the existing literature when we performed a comprehensive literature review. Although many studies deal with CPSs, few papers used an MCDM (Multiple criteria decision making) framework to solve decision-making problems on this issue. More importantly, MCDM approaches used in these papers also have some structural problems and many drawbacks. For example, Silva and Jardim-Goncalves (2021) examined the selection of a more suitable device (system) to perform a task for CPSs with the help of the AHP (Analytic Hierarchy Process) and the PROMETHEE (The Preference Ranking Organization Method for Enrichment Evaluation) combination. Even though this paper has many valuable contributions to the literature, it has some limitations and structural problems. First, the main subject of this study is not the same as the current paper's focal point. Also, the proposed approach has many disadvantages. The AHP is the most commonly criticized MCDM approach since it requires many computations and pairwise comparisons among criteria and decision alternatives. Hence, it has a very complicated basic algorithm, and it may not be reliable for decision-makers, as it suffers from the rank reversal problem (Mufazzal and Muzakkir, 2018). It means any changes in the number of criteria and alternatives or values existing in the indexes may cause dramatic changes in the ranking results. In addition, it requires additional computations for identifying the consistency (Karthikeyan et al., 2016). Besides, it is required to express the preferences and the significances of the criteria on a ratio scale by decision-makers to be able to apply the PROMETHEE technique. Also, the criteria weights denote trade-offs among the selection criteria (Keyser and Peeters, 1996). Therefore, the obtained results by applying this approach may not be realistic and reliable.

Mbuli (2019) evaluated the applicability of the CPS in the railway industry without using any MCDM approach. This study is valuable for the railway industry, but it is limited, as it did not provide an opportunity to compare industries and focus on a single industry. Oliviera et al. (2020) examined the impacts of CPS on Failure Mode and Effect Analysis for the railway industry with the help of Risk Priority Number (RPN) estimation approach. This paper did not also use an MCDM technique, and its managerial implications and contributions are limited with risk assessment.

Jamwal et al. (2021) assessed the applicability of the CPS for the MSMEs (Micro Small Medium Enterprises) sector to develop a sustainability practices framework for Industry 4.0 with the help of a hybrid MCDM technique based on F-AHP (Fuzzy-Analytical hierarchy process) and DEMATEL (Decision making trial and evaluation laboratory). This paper's primary assumption and approach approve the main arguments of the current paper on the difficulties of collecting the crisp values by applying the fuzzy approaches. However, we have indicated the main structural problems and drawbacks of the AHP technique in the previous section; also, the DEMATEL technique has many disadvantages: researchers may have to eliminate some criteria since it has a very complicated and time-consuming basic algorithm;

also, it assumes that each decision-maker have the same experiences, knowledge, and abilities; hence it does not consider the differences among decision-makers (Si et al., 2018).

In addition to these studies, some previous works dealt with smart factories from the perspective of industry 4.0 (Machado et al. 2020; Nujoom et al. 2019; Jiang, 2018; Pascual et al., 2021). However, these papers do not present a robust methodological frame to compare the different industries. In addition, they examined smart factories' impacts on the companies' targets related to accords of requirements of industry 4.0. Besides, they also proposed the traditional MCDM approaches having some structural problems argued above. In addition, Hayhoe et al. (2019) examined the impacts of cross-sector networks of multiple supply chains, cyber-physical production systems on sustainable manufacturing systems, but they did not consider the differences among industries. As is seen above, there are many gaps in the existing literature, and they can be summarised as follows.

- The most of decision techniques used in the previous studies are traditional MCDM approaches. Therefore, these techniques may not provide a flexible decision-making environment to the decision-makers when their structural problems and drawbacks are considered.
- There is no commonly accepted mathematical model used for evaluating the industries concerning the applicability of the CPSs in the production processes.
- Most of the previous works existing in the literature focused on defined subjects such as smart factories, intelligent systems, and sustainable production instead of differences between companies or industries.
- There is no paper dealing with the applicability of CPS for developing the manufacturing processes of heavy industries concerning technology and creating sustainable production systems.

Keeping in mind these gaps and requirements to a comprehensive methodological frame to measure the suitability of the heavy industry branches, the current paper proposes a practical and applicable MCDM framework to fill these gaps and respond to these requirements.

3. THE PROPOSED MCDM FRAMEWORK

Here, we demonstrate the basic algorithm of the new LMAW technique. The proposed MCDM framework has five implementation steps, and these steps are presented as follows (Pamucar et al., 2021). Also, the basic algorithm of the proposed approach is presented in Figure 1.

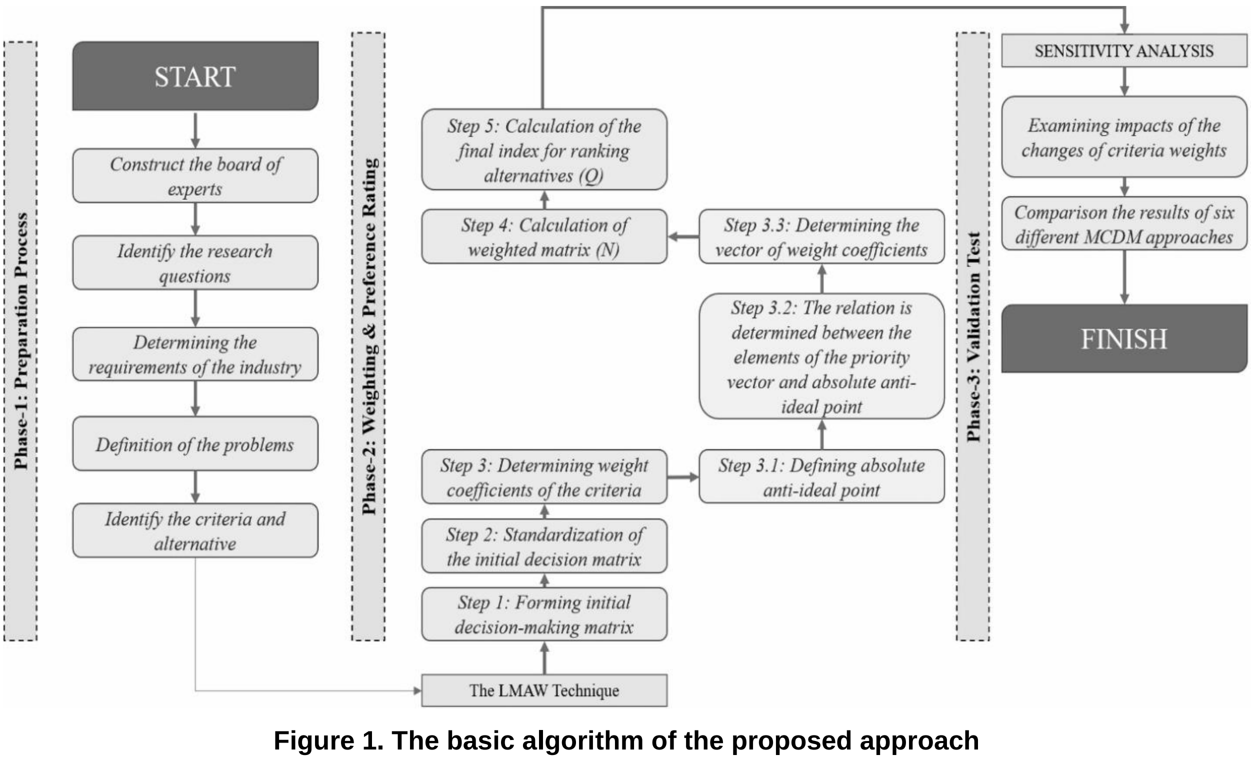

Figure 1. The basic algorithm of the proposed approach

Step 1. Forming initial decision-making matrix: The initial decision matrix is constructed in the first step of the proposed approach. Let suppose m number of alternatives $A = (A_1, A_2, \ldots, A_m)$ and n number of criteria $C = (C_1, C_2, \dots, C_n)$ exist in an evaluation process. In addition, the criteria weight coefficients have to equal 1. Also, k number of decision-makers (experts) $E = (E_1, E_2, \dots, E_k)$ perform evaluations for criteria and decision alternatives. Therefore, the k number of initial decision matrices given in Equation 1 is generated.

$$X^e = \begin{bmatrix} \eta_{11}^e & \eta_{12}^e & \cdots & \eta_{1n}^e \\ \eta_{21}^e & \eta_{22}^e & \cdots & \eta_{2n}^e \\ \cdots & \cdots & \cdots & \cdots \\ \eta_{1m}^e & \eta_{2m}^e & \cdots & \eta_{mn}^e \end{bmatrix} \tag{1}$$

Then, these obtained initial decision matrices are aggregated with the help of the Bonferroni function approach. By applying the mathematical formulation of the Bonferroni function shown in Equation 2, the aggregated initial decision matrix is constructed.

$$\eta_{ij} = \left(\frac{1}{k(k-1)} \sum_{x=1}^{k} \left(\eta_{ij}^{(x)}\right)^p \sum_{\substack{y=1 \\ y \neq x}}^{k} \left(\eta_{ij}^{(y)}\right)^q \right)^{\frac{1}{p+q}} \tag{2}$$

Where η_{ij} presents the averaged values obtained by applying Bonferroni aggregator; $p, q > 0$ present stabilization parameters of the Bonferroni aggregator, while e presents the e^{th} expert $1 \leq e \leq k$ (Pamucar et al. 2021).

Step 2. Standardization of the initial decision matrix: The elements of the aggregated decision matrix are normalized in this step by applying Equation 3. For this purpose, the linear normalization technique is applied by considering the characteristics of the criteria, i.e., benefits "*B*" and cost criteria "*C*". Where; η_j^+ denotes maximum value and η_j^- is the minimum value. Θ_{ij} symbolizes the normalized (Standardized) values of the initial decision matrix.

$$\Theta_{ij} = \begin{cases} \Theta_{ij} = \frac{\eta_{ij} + \eta_j^+}{\eta_j^+} \; if \; C_j \in B \\ \Theta_{ij} = \frac{\eta_{ij} + \eta_j^-}{\eta_{ij}} \; if \; C_j \in C \end{cases} \tag{3}$$

Step 3. Determining weight coefficients of the criteria: In this step, decision-makers evaluate the selection criteria by considering the linguistic evaluation scale given in Table 1.

Table 1. Linguistic evaluation scale for criteria and alternatives

	Criteria		*Alternative*
Scale	*Linguistic terms/Abbreviation*	*Scale*	*Linguistic terms/Abbreviation*
[1.0]	Absolutely low/ [AL]	[1]	Absolutely low/ [AL]
[1.5]	Very low/ [VL]	[2]	Very low/ [VL]
[2.0]	Low/ [L]	[3]	Low/ [L]
[2.5]	Medium/[M]	[4]	Medium/[M]
[3.0]	Equal/ [E]	[5]	Medium High/[MH]
[3.5]	Medium High/[MH]	[6]	High/[H]
[4.0]	High/[H]	[7]	Very high/[VH]
[4.5]	Very high/[VH]		
[5.0]	Absolutely High/[AH]		

Source: Pamucar et al., 2021.

Then, the priority vector is formed as $PV^e = (\gamma_{C1}^e, \gamma_{C2}^e, \dots, \gamma_{Cn}^e)$ γ_{Cn}^e denotes the value obtained from the linguistic scale identified by each expert to criterion$C_t (1 \leq t \leq n)$.

Step 3.1. Defining absolute anti-ideal point: Absolute anti-ideal point is defined in relation to the minimum values from the priority vector and should be lower than the smallest value from the priority vector (Pamucar et al., 2021; Deveci et.al.2021).

Step 3.2. The relation is determined between the elements of the priority vector and the absolute anti-ideal point in this step. Differences between these values are computed with the help of Equation 4.

$$\theta_{Cn}^e = \frac{\gamma_{Cn}^e}{\gamma_{AIP}} \tag{4}$$

Step 3.3. Determining the vector of weight coefficients: The values of weight coefficients of criteria are identified by decision-makers with the help of Equation 5.

$$\omega_j^e = \frac{log_A(\theta_{Cn}^e)}{log_A(b^e)} A > 1 \quad (5)$$

θ_{Cn}^e denotes the elements of relation vector and $b^e = \prod_{j=1}^{n} \theta_j^e$. Also, the condition of being equal to 1 for the sum of criteria weights has to be provided. Then we apply the Bonferroni functions to construct the aggregated weight coefficient vector with the help of Equation 6.

$$\omega_j = \left(\frac{1}{k(k-1)} \sum_{x=1}^{k} \left(\omega_j^{(x)}\right)^p \sum_{\substack{y=1 \\ y \neq x}}^{k} \left(\omega_j^{(y)}\right)^q \right)^{\frac{1}{p+q}} \quad (6)$$

Step 4. Computing the weighted matrix: By implementing Equation 7, the elements of the weighted matrix $Y = [\zeta_{ij}]_{mxn}$ are calculated.

$$\zeta_{ij} = \frac{2\delta_{ij}^{\omega j}}{(2-\delta_{ij})^{\omega j} + \delta_{ij}^{\omega j}} \quad (7)$$

where;

$$\delta_{ij} = \frac{ln(\Theta_{ij})}{ln(\prod_{i=1}^{m} \Theta_{ij})} \quad (8)$$

where; Θ_{ij} denotes the normalized matrix elements and ω_j symbolizes the criteria weights coefficient.

Step 5. Calculation of the final index for ranking alternatives (Q_i): the final index for alternatives defining the preference ratings of options is identified by applying Equation 9.

$$Q_i = \sum_{j=1}^{n} \zeta_{ij} \quad (9)$$

4. EVALUATION OF THE HEAVY INDUSTRY BRANCHES

In this section, the proposed dynamic MCDM framework consisting of three phases was applied to evaluate the potential of transformation from the traditional production system to CPSs for the branches of heavy industry.

4.1. The Preparation Process

For this purpose, a board of experts consisting of five highly experienced and have deep knowledge professionals was constructed to ask their opinion on this issue during the research process. Details of these experts are presented in Table 2.

Table 2. Details of the members of the board of experts

DMs	*Graduation*	*Degree*	*Duty*	*Experience*
DM^1	Industrial Engineering	Master's degree	Project Manager	12
DM^2	Mechanical Engineering	Undergraduate	General Manager	18
DM^3	Industrial Engineering	Undergraduate	Product Manager	13
DM^4	Business	Undergraduate	System designer	17
DM^5	Industrial Engineering	Undergraduate	Supply Chain Man.	20

Table 3. The selection criteria and decision alternatives

Code	*Direction*	*Criteria*	*Code*	*Alternatives*
C_1	Max	First Pass yield	A_1	Aerospace
C_2	Max	Throughput Rate	A_2	Shipbuilding
C_3	Max	Availability	A_3	Mining
C_4	Min	Downtime	A_4	Machine tool building
C_5	Max	Overall Equipment Effectiveness (OEE)	A_5	Locomotive manufacturing
C_6	Min	Energy consumption	A_6	Oil and gas
C_7	Min	Scrap ratio	A_7	Steel production
C_8	Max	Target	A_8	Chemical production
C_9	Max	Count	A_9	Construction of large buildings and infrastructure
C_{10}	Min	Takt Time		

Then, existing literature was reviewed, and the selection criteria and decision alternatives were identified together with the experts. For this purpose, researchers and decision-makers decided to use the set of key performance indicators (KPI) in the ISO 22400-2:2014 Automation systems and integration published by the International Standardisation Organisation as the set of selection criteria. Also, the branches of heavy industry were selected as the decision alternatives. The selection criteria and decision alternatives are presented in Table 3.

The definitions of the criteria given in Table 3 are presented as follows. C_1 yield refers to the percentage of products that meet quality requirements from the total of inspected products (IP). Products that meet quality requirements are named good products (GP). C_2 is the performance of the production process. The calculation compares produced quantity (PQ) with actual order execution time (AOET). C_3 is the availability shows the actual time the equipment is available for usage. The calculation compares the actual utilized time (OPT) with the loading time (LT). C_4 is the result of a breakdown or simply a machine changeover. When machines are not operating, the company can be at risk of loss.

C_5 combines the availability, the effectiveness, and the finished goods ratio. The produced index indicates the efficiency of machines or complete assembly lines. C_6 is the ratio of energy consumed per production cycle (E) in comparison to the produced quantity (PQ). C_7 is the ratio of scrap quantity (SQ) in comparison to the produced quantity (PQ). C_8 is target and many organizations display target values for output, rate, and quality. This KPI helps motivate employees to meet specific performance targets. C_9 relates to the amount of product produced. The count typically refers to the product produced since the last machine changeover or the production sum for the entire shift or week. C_{10} is the amount of time, or cycle time, to complete a task.

When it is considered that expectations of all industries and companies concerning industry 4.0 and digital transformation processes are not clear sufficiently, collecting data on this issue is not easy. In addition, data publishing habits of almost all companies do not exist except corporate companies. Therefore, no commonly accepted measurement system can help to collect crisp data in the related field. Because of that, while subjective evaluations were performed for criteria by decision-makers by considering the nine-point scale, the seven-point scale was used for evaluating the decision alternatives.

4.2. Implementation of the LMAW Technique

After the phases of the preparation process are completed, the basic algorithm of the LMAW techniques that is the proposed approach in the current paper is followed. Linguistics evaluations of the experts are presented in Appendix 1. Then, the initial decision matrix is generated in the first implementation step of the model, as presented in Table 4.

Table 4. Aggregated decision matrix

Alternatives	*Criteria 1*	*Criteria 2*	*Criteria 3*	*Criteria 4*	*Criteria 5*	*Criteria 6*	*Criteria 7*	*Criteria 8*	*Criteria 9*	*Criteria 10*
Alt.-1	6.595	6.993	5.797	2.145	6.797	5.394	6.588	1.761	6.797	2.793
Alt.-2	5.992	5.394	5.983	1.732	5.586	5.992	5.595	2.793	7.000	3.391
Alt.-3	2.588	2.569	1.581	5.394	6.595	3.937	1.549	7.000	5.586	6.181
Alt.-4	3.347	4.593	5.394	5.385	5.797	3.391	5.394	5.177	5.595	5.187
Alt.-5	4.123	4.123	4.000	4.393	2.191	3.194	4.382	3.000	5.394	2.145
Alt.-6	4.583	5.779	2.569	7.000	5.196	5.595	5.788	6.387	6.173	6.588
Alt.-7	5.788	6.000	6.395	5.779	5.797	3.194	5.797	4.171	5.797	5.586
Alt.-8	4.393	3.391	5.196	6.595	6.197	4.561	5.394	6.387	6.387	5.779
Alt.-9	3.271	6.197	6.797	5.779	6.993	2.366	2.757	5.394	5.595	6.387

For example, the numerical value of η_{11} that is the first element of the initial decision matrix is calculated by computing the Bonferonni mean of the preferences of the five decision-makers $[\eta_{11} = \{VH, VH, H, VH, H\} = \{7,7,6,7,6\}]$ with the help of Equation 2 as follows.

$$\eta_{11}{}^{p=q=1} = \left(\frac{1}{5(5-1)}(7^1.7^1 + 7^1.6^1 + 7^1.7^1 + 7^1.6^1 + \ldots + 6^1.7^1 + 6^1.7^1 + 6^1.6^1 + 6^1.7^1)\right)^{1/2} = 6.595$$

After the initial decision matrix is generated, these matrix elements are normalized with the help of Equation 3. For this purpose, characteristics of the criteria are considered, and the normalized matrix is presented in Table 5.

Table 5. Normalized decision matrix

Alternatives	*Criteria 1*	*Criteria 2*	*Criteria 3*	*Criteria 4*	*Criteria 5*	*Criteria 6*	*Criteria 7*	*Criteria 8*	*Criteria 9*	*Criteria 10*
Alt.-1	2.000	2.000	1.853	1.808	1.972	1.439	1.235	1.252	1.971	1.768
Alt.-2	1.908	1.771	1.880	2.000	1.799	1.395	1.277	1.399	2.000	1.632
Alt.-3	1.392	1.367	1.233	1.321	1.943	1.601	2.000	2.000	1.798	1.347
Alt.-4	1.507	1.657	1.794	1.322	1.829	1.698	1.287	1.740	1.799	1.414
Alt.-5	1.625	1.590	1.588	1.394	1.313	1.741	1.354	1.429	1.771	2.000
Alt.-6	1.695	1.826	1.378	1.247	1.743	1.423	1.268	1.912	1.882	1.326
Alt.-7	1.878	1.858	1.941	1.300	1.829	1.741	1.267	1.596	1.828	1.384
Alt.-8	1.666	1.485	1.764	1.263	1.886	1.519	1.287	1.912	1.912	1.371
Alt.-9	1.496	1.886	2.000	1.300	2.000	2.000	1.562	1.771	1.799	1.336

The values of Θ_{11} and Θ_{14}existing in the normalized matrix are calculated as follows.

$$\Theta_{11}=\left(\frac{(6.595+max(6.595;5.992;2.588;3.347;4.123;...;3.271))}{max(6.595;5.992;2.588;3.347;4.123;...;3.271)}\right)=2.000$$

$$\Theta_{14}=\left(\frac{(2.145+min(2.145;1.732;5.394;5.385;4.393;...;5.779))}{2.145}\right)=1.808$$

Next, the weight coefficients of criteria are determined by decision-makers by considering the nine-point scale given in Table 1. The determined linguistic evaluations are presented in Table 6.

Table 6. Evaluating the criteria by decision-makers

	Linguistic evaluations		*Numerical rating*
Criteria	*Decision makers evaluation ($DM^1,DM^2,\ldots,DM^5$)*	*Criteria*	*Decision makers evaluation ($DM^1,DM^2,\ldots,DM^5$)*
C_1	[H;H;VH; H;H]	C_1	[4;4;4.5;4;4]
C_2	[VH; L;VH; VH; VH]	C_2	[4.5;2;4.5;4.5;4.5]
C_3	[H;H;M;M;H]	C_3	[4;4;2.5;2.5;4]
C_4	[M;VL; M;M;H]	C_4	[2.5;1.5;2.5;2.5;4]
C_5	[AH; AH; H;AH; AH]	C_5	[5;5;4;5;5]
C_6	[H;VL; H;VL; H]	C_6	[4;1.5;4;1.5;4]
C_7	[VL; M;M;AL; VL]	C_7	[1.5;2.5;2.5;1;1.5]
C_8	[H;M;H;VL; H]	C_8	[4;2.5;4;1.5;4]
C_9	[M;H;H;H;M]	C_9	[2.5;4;4;4;2.5]
C_{10}	[VL; M;M;H;H]	C_{10}	[1.5;2.5;2.5;4;4]

After five priority vectors presented in Table 6 are formed, the relation between each element of these vectors and absolute anti ideal point (AIP) are identified. For this purpose, AIP is accepted as γ_{AIP}=0.5, and calculated values are presented in Table 7.

Table 7. The relation between each element of priority vectors and the absolute anti ideal point

Decision Makers	Priority vector elements $\gamma_{Cn}:(\gamma_{C1},\gamma_{C2},...,\gamma_{C10})$	Relation vector elements $\theta_{Cn}:(\theta_{C1},\theta_{C2},...,\theta_{C10})$
DM^1	[4.0;4.5;4.0;2.5;5.0;4.0;1.5;4.0;2.5;1.5]	[8;9;8;5;10;8;3;8;5;3]
DM^2	[4.0;2.0;4.0;1.5;5.0;1.5;2.5;2.5;4.0;2.5]	[8;4;8;3;10;3;5;5;8;5]
DM^3	[4.5;4.5;2.5;2.5;4.0;4.0;2.5;4.0;4.0;2.5]	[9;9;5;5;8;8;5;8;8;5]
DM^4	[4.0;4.5;2.5;2.5;5.0;1.5;1.0;1.5;4.0;4.0]	[8;9;5;5;10;3;2;3;8;8]
DM^5	[4.0;4.5;4.0;4.0;5.0;4.0;1.5;4.0;2.5;4.0]	[8;9;8,8;10;8;3;8;5;8]

For example, the relation between priority vector elements identified by DM^1 and the absolute anti ideal point is calculated as follows.

$\theta^{DM^1}_{(\theta_{C1},\theta_{C2},...,\theta_{C10})} = \left[\left(\frac{4.0}{0.5};\frac{4.5}{0.5};\frac{4.0}{0.5};\frac{2.5}{0.5};\frac{5.0}{0.5};\frac{4.0}{0.5};\frac{1.5}{0.5};\frac{4.0}{0.5};\frac{2.5}{0.5};\frac{1.5}{0.5}\right)\right] = [(8;9;8;5;10;8;3;8;5;3)]$

Then, by applying Equation 5, each decision-maker determined weights coefficients of criteria, and these vectors are aggregated with the help of the Bonferroni aggregating function (Equation 6). Next, the final weight coefficient for each criterion is presented in Table 8.

Table 8. The final criteria weight coefficients

Weights	*Criteria 1*	*Criteria 2*	*Criteria 3*	*Criteria 4*	*Criteria 5*	*Criteria 6*	*Criteria 7*	*Criteria 8*	*Criteria 9*	*Criteria 10*
ω^1	0.114	0.121	0.114	0.088	0.126	0.114	0.060	0.114	0.088	0.060
ω^2	0.123	0.082	0.123	0.065	0.136	0.065	0.095	0.095	0.123	0.095
ω^3	0.115	0.115	0.084	0.084	0.109	0.109	0.084	0.109	0.109	0.084
ω^4	0.123	0.130	0.096	0.096	0.137	0.065	0.041	0.065	0.123	0.123
ω^5	0.106	0.112	0.106	0.106	0.117	0.106	0.056	0.106	0.082	0.106
$\omega^{\text{aggregated weights}}$	0.1161	0.1115	0.1042	0.0874	0.1248	0.0910	0.0665	0.0973	0.1046	0.0931
Rank	2	3	5	9	1	8	10	6	4	7

For instance, ω^1 for DM[1] given in Table 8 was computed as follows.

$$\omega^1 = \left[\left(\frac{ln(8)}{ln(8x9x8...x3)}\right),\left(\frac{ln(9)}{ln(8x9x8...x3)}\right),\left(\frac{ln(8)}{ln(8x9x8...x3)}\right),...,\left(\frac{ln(3)}{ln(8x9x8...x3)}\right)\right] = [(0.114,0.121,0.114,...,,0.060)]$$

For remain four decision-makers, Equation 5 is applied similarly, and the final weight coefficients ω^2,ω^3,ω^4ve $\omega^5$are computed. Then, the Bonferroni function was applied for aggregating the weight coefficients of criteria. For example, the final weight coefficient of the C_1 criterion was computed as follows.

$$\omega_1^{\text{aggregated weights}} = \left(\frac{1}{5(5-1)}(0.114^1.0.123^1 + 0.114^1.0.115^1+...+0.106^1.0.123^1)\right)^{1/2} = 0.1161$$

Next, the weighted normalized matrix was constructed with the help of Equations 7 and 8 for determining the preference rating of the decision alternatives. The obtained results are presented in Table 9.

Table 9. Weighted normalized matrix

Alternatives	*Criteria 1*	*Criteria 2*	*Criteria 3*	*Criteria 4*	*Criteria 5*	*Criteria 6*	*Criteria 7*	*Criteria 8*	*Criteria 9*	*Criteria 10*
Alt.-1	0.855	0.859	0.862	0.901	0.834	0.859	0.892	0.824	0.858	0.886
Alt.-2	0.851	0.847	0.863	0.909	0.825	0.855	0.897	0.843	0.859	0.879
Alt.-3	0.811	0.813	0.805	0.866	0.833	0.871	0.934	0.880	0.850	0.855
Alt.-4	0.824	0.840	0.859	0.867	0.827	0.877	0.898	0.868	0.850	0.862
Alt.-5	0.834	0.835	0.846	0.874	0.777	0.879	0.904	0.846	0.848	0.896
Alt.-6	0.838	0.850	0.827	0.856	0.821	0.858	0.896	0.876	0.854	0.852
Alt.-7	0.849	0.852	0.866	0.864	0.827	0.879	0.896	0.860	0.851	0.859
Alt.-8	0.837	0.826	0.857	0.859	0.830	0.866	0.898	0.876	0.855	0.857
Alt.-9	0.822	0.853	0.868	0.864	0.836	0.890	0.918	0.870	0.850	0.853

ζ_{11}, the first element of the weighted normalized decision matrix is calculated as follows.

$$\delta_{11} = \left[\left(\frac{ln(2.00)}{ln[(2.00)x(1.908)x...x(1.496)]}\right)\right] = 0.149;$$

$$\zeta_{11} = \left[\left(\frac{2x((0.149)^{0.1161})}{(2-0.149)^{0.1161}+0.149^{0.1161})}\right)\right] = 0.855$$

In the final implementation step of the proposed model, the final index values of the decision alternatives were calculated by applying Equation 9. The computed final index values for decision alternatives are presented as follows.

$Q_1 = (0.855 + 0.859 + 0.862+...+0.886) = 8.630$ $Q_5 = (0.834 + 0.835 + 0.846+...+0.896) = 8.541$

$Q_2 = (0.851 + 0.847 + 0.863+...+0.879) = 8.628$ $Q_6 = (0.838 + 0.850 + 0.827+...+0.852) = 8.529$

$Q_3 = (0.811 + 0.813 + 0.805+...+0.855) = 8.518$ $Q_7 = (0.849 + 0.852 + 0.866+...+0.859) = 8.602$

$Q_4 = (0.824 + 0.840 + 0.859+...+0.862) = 8.571$ $Q_8 = (0.837 + 0.826 + 0.857+...+0.857) = 8.561$

$Q_9 = (0.822 + 0.853 + 0.868 + \ldots + 0.853) = 8.625$

By considering these values, the final ranking performances of the options are obtained as presented in Table 10.

Table 10. Ranking the alternatives concerning the final index values

Alternatives	*Alt.-1*	*Alt.-2*	*Alt.-3*	*Alt.-4*	*Alt.-5*	*Alt.-6*	*Alt.-7*	*Alt.-8*	*Alt.-9*
Q_i	8.630	8.628	8.518	8.571	8.541	8.529	8.602	8.561	8.625
Rank	1	2	9	5	7	8	4	6	3

4.3. Validation Test

In this section, a comprehensive sensitivity analysis consisting of two phases was performed to test the applicability and validity of the proposed approach and its obtained results. In the first stage, the impacts of changing the criteria weights on the ranking results were examined. Next, we applied five popular MCDM techniques and compared the results obtained using both the proposed approach and others.

In the first stage, we changed the weight of each criterion in each scenario to examine the impacts of modification of criteria weights on the ranking results. For this purpose, we formed 100 different scenarios and reduced criteria weight at the rate of 10% in each scenario. Then, we continued to reduce the weight for the criterion till the criterion weight was equal to zero. Previous works suggested changing the weights of criteria in the first three ranks (Stankovic et al. 2020). This kind of approach can give a limited result since it did not consider the potential impacts of changes in the remaining criteria' weights. The current paper proposes to include all criteria into the analyzing process by following the implementation proposed by Görçün et al. (2021). According to the algorithm proposed by them, the criterion weight is changed at the rate of 10%. Then, the weights of the remaining criteria are corrected for providing the condition that the sum of weights should be equal to 1. The new weights of the criteria are identified by applying Eqs. 10, 11, and 12.

$$w_{fv}^{1} = w_{pv}^{1} - \left(w_{pv}^{1} . m_v\right) \tag{10}$$

$$w_{nv}^{2} = \frac{\left(1 - w_{fv}^{1}\right)}{n-1} + w_{pv}^{2} \tag{11}$$

$$w_{fv}^{1} + \sum w_{nv}^{2} = 1 \tag{12}$$

Here, w_{fv}^{1}denotes the new value of the modified weight of j^{th} factor, $w_{pv}^{1}$is the previous values of the criterion, $m_v$is the modification degree in terms of percentage (i.e., 10%, 20%,...,100%). Also, w_{nv}^{2}symbolizes new values of remaining factors, n is the number of factors, w_{pv}^{2} is the previous values of the remaining criteria. Then, we followed the basic algorithm of the first phase and obtained the new ranking results for all scenarios presented in Figure 2.

Figure 2. Impacts of changing the criteria weights on the ranking results

As shown in Figure 2, Alt.-1, the best option, has remained the best alternative in 50 scenarios. It has been slight changes, which cannot change the overall results in ranking performances of the alternatives. The average similarity rate between the proposed model results and the results obtained by different 100 scenarios is determined as 72%. In the second phase, we implemented five different popular MCDM approaches such as MARCOS (Stević et al., 2020), MAIRCA (Gigović et al., 2016), WASPAS (Zavadskas et al., 2012), MABAC (Pamučar and Ćirović,2015), and MAUT (Lopes and Almeida, 2015). According to the obtained results, ranking results of all popular techniques and the proposed approach are similar to a high degree. The ranking results of the techniques, including the proposed approach, are presented as follows.

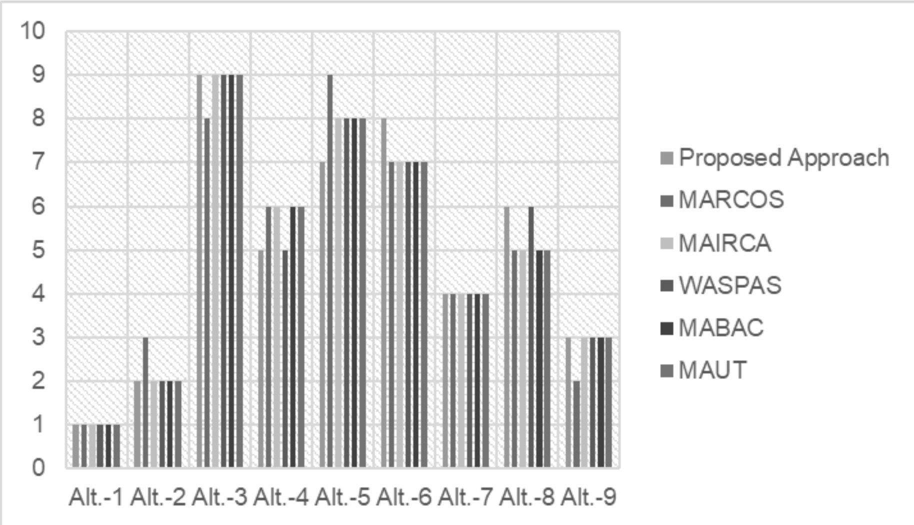

Figure 3. Comparison of the ranking results of the proposed approach and others

As is seen in Figure 3, Alt.-1 has remained the best option for all popular implemented techniques and the LMAW technique, and the ranking position of the Alt.-7 has not also changed. Besides, it has been observed minor changes in the ranking positions of some alternatives; however, these changes cannot change the overall results.

5. CONCLUSION

Determining the primary areas in the heavy industries is crucial for policymakers since the appropriate investment decision and source utilization is essential for countries, individuals, and companies. It can allow creating more productive and efficient industries in countries. Moreover, evaluating and selecting appropriate fields in heavy industries is not easy for decision-makers. So indeed, no papers are dealing with this issue directly, and we noticed severe and surprising gaps in the existing literature. Furthermore, the previous paper existing in the literature did not propose an applicable and practical evaluation technique for assessing the suitability of the heavy industry branches to the CPS use in the production systems. The current paper proposes an applicable and practical MCDM framework to evaluate the heavy industry branches by keeping the industry's requirements and existing gaps in the literature.

When the obtained results are evaluated in detail, it has been observed that the proposed approach has the potential to fill the gaps existing in the literature. Also, it is resistant to the rank reversal problem because it is maximally stable and consistent than other popular and traditional MCDM approaches (Pamucar et al., 2021). Hence, we can accept that the LMAW method is a reliable MCDM framework for decision-makers. It can process subjective and objective criteria. In addition, the paper has valuable contributions to the literature as follows. It helps identify the heavy industry's prior branches concerning digital transformation suitability in their production systems and processes.

According to the obtained results, C_5, Overall Equipment Effectiveness (OEE), is the most crucial criterion for evaluating the branches of the heavy industry. It is reasonable and realistic because OEE (Overall Equipment Effectiveness) is defined as the critical indicator for identifying the efficiency and productivity of a production system. It helps to detect and solve any problem that occurred in the production process, and it provides an opportunity to prepare a manufacturing system for digital transformation. It is impossible to create a well-functioned production system supported with CPSs if there are problems in the production systems. Therefore, it serves to construct an excellent production system for companies and industries.

C_1 First Pass Yield has been determined as the second crucial factor in evaluating the industries concerning the suitability of using the CPS in production processes. It is meaningful since it is an essential metric for measuring a manufacturing system's performance, productivity, and efficiency. Also, it is a good indicator of the effectivity of a manufacturing system, and it can help eliminate waste of time and sources. Other criteria were ranked as $C_2 > C_9 > C_3 > C_8 > C_{10} > C_6 > C_4 > C_7$.

When we evaluate the results of the proposed model for determining the preference ratings of the alternatives, Alt.-1, Aerospace industry is the best alternative, and Alt.-2 Shipbuilding industry is the second-best option and follows to first alternatives. Remainders have been ranked as Alt.-9> Alt.-7> Alt.-4> Alt.-8> Alt.-5> Alt.-6> Alt.-3. These results are reasonable and realistic, as the Aerospace and shipbuilding industry respond to requirements to identify the priority of the heavy industry branches.

In addition, the obtained results were tested with the help of a comprehensive sensitivity analysis, and the results of the analysis approve the validity and applicability of the proposed approach. Hence, the results of the proposed LMAW techniques can be accepted as accurate, reasonable, and reliable.

The current paper proposes a methodological frame to solve very complicated and time-consuming decision-making problems. Also, the proposed LMAW technique can be implemented to solve various decision-making problems encountered in many fields and evaluate the suitability of the heavy industry branches to digital transformation and using CPS in their production processes. Decision-makers and policymakers who try to manage the technological industrialization policies of countries can apply this methodological frame in an evaluation process to assess the industries, as it has an efficient and applicable basic algorithm. In addition, it can be inspirational for authors who carry out future works on this issue.

In addition to the methodological implications of the proposed MCDM approach, the paper has some valuable managerial implications. The managerial implications of the paper can be summarised as follows.

- It provides opportunities for prioritizing which branches of the heavy industry should be supported and incented primarily for decision-makers and practitioners. Therefore, it can be a practical tool for evaluating the branches of heavy industry for suitability of the sectors for digital transformation and effectively using CPSs in these industries' production systems.
- It also presents an applicable, robust, and powerful methodological frame to make self-evaluation for their companies comparatively. Thus, decision-makers can apply the proposed model for evaluating their companies concerning the property of these companies.

The LMAW technique proposed in the current paper can be extended with the help of different fuzzy MCDM frameworks. Also, new criteria that occur in the future depending on changing industries' requirements can be included in the scope of the studies by future studies.

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Appendix. Linguistic evaluations performed by DMs for the Alternatives

Alternatives	*DMs*	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
Alt.1	DM1	VH	H	H	AL	H	MH	H	L	VH	VL
	DM2	VH	VH	MH	L	VH	MH	H	VL	VH	L
	DM3	H	VH	H	L	VH	MH	H	VL	H	L
	DM4	VH	VH	H	L	VH	H	H	AL	VH	L
	DM5	H	VH	H	AL	VH	H	VH	AL	VH	L
Alt.2	DM1	MH	H	MH	AL	MH	MH	H	L	VH	M
	DM2	H	H	VH	AL	MH	H	MH	VL	VH	M
	DM3	H	MH	MH	L	VH	H	MH	L	VH	L
	DM4	VH	MH	VH	AL	MH	VH	H	L	VH	L
	DM5	H	MH	H	L	H	H	H	L	VH	L
Alt.3	DM1	L	L	VL	MH	VH	M	AL	VH	VH	MH
	DM2	L	AL	VL	MH	VH	MH	VL	VH	H	VH
	DM3	VL	L	AL	MH	VH	H	L	VH	MH	VH
	DM4	VL	L	VL	H	H	L	AL	VH	MH	MH
	DM5	L	L	AL	H	H	VL	AL	VH	MH	VH
Alt.4	DM1	M	M	MH	MH	H	M	MH	M	H	MH
	DM2	M	M	MH	MH	H	L	H	H	H	MH
	DM3	AL	MH	MH	VH	H	M	MH	H	MH	H
	DM4	M	MH	H	MH	H	L	MH	M	MH	H
	DM5	M	MH	H	MH	MH	L	H	H	H	M
Alt.5	DM1	MH	MH	M	MH	VL	L	H	L	MH	AL
	DM2	MH	AL	M	MH	VL	M	M	L	MH	L
	DM3	MH	MH	M	M	L	L	M	L	MH	L
	DM4	AL	MH	M	M	VL	L	M	L	H	L
	DM5	MH	MH	M	M	VL	L	M	L	H	AL
Alt.6	DM1	H	VH	L	VH	MH	H	H	VH	H	VH
	DM2	M	MH	L	VH	MH	H	MH	VH	M	VH
	DM3	M	MH	AL	VH	MH	MH	H	H	VH	VH
	DM4	M	VH	L	VH	MH	MH	MH	MH	VH	MH
	DM5	MH	MH	L	VH	H	H	VH	VH	VH	VH
Alt.7	DM1	VH	H	VH	MH	H	L	MH	M	H	H
	DM2	H	H	H	VH	H	L	H	H	H	H
	DM3	H	H	VH	MH	MH	M	H	M	MH	H
	DM4	MH	H	H	VH	H	L	H	M	H	H
	DM5	MH	H	H	MH	H	L	H	L	H	M
Alt.8	DM1	MH	M	MH	VH	H	M	MH	VH	VH	MH
	DM2	MH	M	MH	H	H	M	H	VH	MH	VH
	DM3	M	L	MH	VH	H	VH	MH	MH	H	VH
	DM4	M	L	H	VH	H	M	H	H	VH	MH
	DM5	M	L	MH	H	VH	M	MH	VH	VH	MH
Alt.9	DM1	VH	H	H	VH	VH	VL	M	MH	H	VH
	DM2	VL	VH	VH	H	VH	VL	VL	MH	H	MH
	DM3	VL	H	VH	H	H	M	VL	MH	MH	VH
	DM4	L	H	VH	M	H	VL	VL	H	MH	VH
	DM5	L	H	VH	H	H	VL	M	H	H	H