Journal of Operations Intelligence, Volume 4, Issue 1 (2026) 23-41

Journal of Operations Intelligence

Journal homepage: www.jopi-journal.org
eISSN: 3009-4267

Evaluation of AI Tools in Terms of Sustainable Workforce Productivity and Their Impact on Organizational Outcomes Using an Intuitionistic Fuzzy Approach

Adis Puška[1], Jurica Bosna[2], Darko Božanić[3*]

[1] Department of Public Safety, Government of Brčko District of Bosnia and Herzegovina, Brčko, Bosnia and Herzegovina
[2] Department of Economics, University of Zadar, Zadar, Croatia
[3] Military Academy, University of Defence in Belgrade, Belgrade, Serbia

ARTICLE INFO

Article history:
Received 19 March 2026
Received in revised form 28 May 2026
Accepted 6 July 2026
Available online 15 July 2026

Keywords:
AI tools; Sustainable productivity; Intuitionistic fuzzy approach; SWARA method; MABAC method.

ABSTRACT

The adoption of artificial intelligence (AI) offers significant opportunities to improve organizational performance. However, organizations must leverage its potential to enhance productivity without compromising employees' long-term well-being. This study addresses this challenge by developing a multi-criteria decision-making framework for evaluating six AI tools against eight sustainability-oriented criteria. Expert judgments provided by academic researchers from the Republic of Croatia were used to assess both the importance of the evaluation criteria and the performance of the AI tools in supporting sustainable organizational efficiency. Given the uncertainty and imprecision inherent in expert evaluations, an intuitionistic fuzzy framework was employed. The SWARA (Stepwise Weight Assessment Ratio Analysis) method was applied to determine the criteria weights, while the MABAC (Multi-Attributive Border Approximation Area Comparison) method was used to rank the AI tools. The results indicate that improving individual productivity and enhancing employee engagement and motivation are the most influential evaluation criteria. The findings further show that AI tools supporting employee learning and development, together with decision-support capabilities, represent the most suitable solutions for sustainable organizational efficiency. The robustness of the proposed framework was confirmed through comparative and sensitivity analyses. The study provides practical guidance for managers seeking to balance technological advancement with the long-term development and well-being of human resources.

1. Introduction

The rapid implementation of artificial intelligence (AI) in organizations is transforming the way employees perform operational tasks. Generative AI, process automation, decision-support systems, and algorithmic performance monitoring are becoming integral parts of everyday work.

* *Darko Božanić*
E-mail address: dbozanic@yahoo.com

https://doi.org/10.31181/jopi41202665

Research shows that AI can increase productivity and work quality [1, 2]; however, at the same time, questions arise regarding long-term effects on autonomy, cognitive load, and the risk of burnout. The development of algorithmic management introduces new forms of work control and coordination [3, 4]. From the perspective of the Job Demands & Resources model [5, 6], AI tools can function both as resources (increasing efficiency, reducing errors) and as demands (work intensification, technostress). Therefore, productivity cannot be observed solely through short-term operational results, but also through their impact on employee well-being and organizational stability.

The literature on sustainable human resource management emphasizes the need to balance the economic and social goals of organizations [7, 8]. However, existing AI research generally does not differentiate between specific groups of tools nor integrate the effects on productivity and well-being into a single evaluation framework. The evaluation of AI tools is burdened by subjectivity and uncertainty in expert assessments, since the long-term organizational outcomes of AI implementation remain uncertain. For this reason, uncertainty arises among experts when assessing AI tools, as they cannot precisely determine the extent to which a particular AI tool meets the organization's defined goals, especially because such evaluations rely on qualitative data. When managers make decisions about the adoption of AI tools, they often rely on their own experience or on partial analyses available to them [9]. Decision-making in this manner leads to uncertain outcomes, where short-term efficiency gains are achieved at the expense of long-term employee well-being and organizational sustainability. Maintaining long-term sustainability in organizations is therefore critically important [10].

The motivation for conducting this research stems from the lack of a structured, analytical tool that would enable experts to make informed decisions. As a result, decision-making is burdened by uncertainty and imprecision, particularly in assessing future organizational outcomes, as companies encounter new tools that have not been previously used. Therefore, the evaluation of AI tools should be conducted according to criteria that integrate different dimensions of organizational performance. To achieve this, it is necessary to apply multicriteria decision-making (MCDM) methods; furthermore, to incorporate uncertainty and imprecision into the decision-making process, an intuitionistic approach should be applied, as it enables the inclusion of uncertainty and imprecision in the evaluation process [11-13]. The application of this approach provides a more robust and reliable basis for decision-making.

The main objective of this research is to develop and apply a multi-criteria model of expert evaluation that enables the ranking of AI tools according to sustainable productivity, with explicit inclusion of uncertainty and imprecision in expert assessments. Specific objectives include: (1) operationalizing the concept of sustainable productivity through the establishment of criteria that encompass different organizational dimensions; (2) applying an intuitionistic approach and MCDM methods to determine criteria weights and rank AI tools; (3) identifying AI tools that represent an optimal balance between operational efficiency and employee's benefit, and providing recommendations for practice.

Based on this, the main research question is defined as follows: Which AI tool contributes most to sustainable organizational productivity according to expert evaluation? To answer this question, the following specific research questions are posed: (1) what are the key criteria for evaluating the contribution of AI tools to sustainable productivity, and what is their relative importance? (2) How are AI tools ranked according to these criteria when expert uncertainty and imprecision are considered? (3) What implementation guidelines emerge from the results obtained?

The expected contribution of the research is twofold. From a theoretical perspective, the paper redefines the concept of productivity in the context of AI by integrating organizational dimensions into a unified evaluation framework, thereby addressing the need for technology evaluation within organizations. From a methodological perspective, the application of the intuitionistic approach within the MCDM framework enables the treatment of uncertainty and imprecision present in expert assessments, particularly regarding long-term organizational outcomes. From a practical perspective, the results will provide managers and decision-makers with a structured tool for the selection and implementation of AI technologies, thereby reducing the risk of unbalanced decisions that prioritize short-term efficiency at the expense of long-term organizational sustainability.

The paper is structured as follows. Following the introduction, the second chapter provides a literature review on the effects of AI on work, algorithmic management, the Job Demands & Resources model, as well as sustainable productivity and MCDM approaches. The third chapter describes the methodology, including the differentiation of AI tools, the definition of criteria, and the application of the intuitionistic approach and MCDM methods. The fourth chapter presents the evaluation results and additional analyses, while the fifth chapter discusses the findings and their implications, with a review of the limitations and guidelines of this research. The sixth chapter presents the conclusions of the conducted study.

2. Literature Review

2.1 AI and the Changing Nature of Work

The discussion of the effects of AI on work and productivity starts from the relationship between automation and labor demand [14]. Autor [15] shows that technology does not necessarily reduce employment in the long term, since the substitution of routine tasks leads to the creation of new activities and changes in the structure of skill demand. Acemoglu and Restrepo [16] emphasize that the effects depend on the balance between the labor substitution effect and the creation of new tasks, with the institutional context shaping the distribution of gains. Raisch and Krakowski [17] further deepen this tension through the paradox of automation and augmentation, highlighting challenges in redefining decision-making processes and control. At the micro level, Brynjolfsson, Li, and Raymond [2] provide empirical evidence that generative AI can increase productivity, but with heterogeneous effects depending on the type of work and skill level. The results of this research are important because they imply that the impact of AI cannot be generalized but must be analyzed according to specific tools and organizational needs. Based on this, this paper differentiates six AI tools, enabling the evaluation of their effects on sustainable productivity.

2.2 Algorithmic Management and the Psychological Consequences of AI

AI is increasingly associated with algorithmic management and new forms of surveillance. Kellogg, Valentine, and Christin [3] emphasize that algorithms simultaneously enable coordination and intensify control, while Meijerink and Bondarouk [4] highlight their dual role in human resource management. Ball [18] and Ravid *et al.,* [19] show that electronic performance monitoring can have both positive and negative effects, depending on system design and perceptions of fairness, which is particularly relevant for AI monitoring tools. The psychological and organizational consequences of AI can be interpreted through the Job Demands & Resources model [5, 6], according to which tools can function both as resources (increasing efficiency, reducing workload) and as demands (work intensification, stress). Schaufeli *et al.,* [20] distinguish between burnout and engagement, while Tarafdar *et al.,* [21] introduce the concept of technostress, emphasizing the importance of technology design in shaping outcomes. This duality is crucial for the conceptualization of criteria in this paper, which must encompass both the positive and negative effects of AI tools on employees.

2.3 Sustainable Productivity and Sustainable Human Resource Management

The concept of sustainable productivity is theoretically grounded in the literature on sustainable work systems and sustainable human resource management. Docherty *et al.,* [22] emphasize the integration of efficiency and social sustainability; Ehnert [7] and Kramar [8] highlight the need to balance performance and the preservation of human resources, while Mariappanadar [23] warns about the hidden costs of excessive efficiency. Shneiderman [24] further normatively directs evaluation through the concept of human-centered AI, according to which technological solutions should support long-term well-being and trust.

Sheeran *et al.,* [25] show that sustainability mediates the relationship between well-being and work performance. Ramgolam *et al.,* [26] emphasize the importance of green and socially responsible sustainable human resource management for sustainable employee performance. Jiang *et al.,* [27] link sustainable human resource management with productivity through efficiency and quality. Islam *et al.,* [28] demonstrate that green sustainable human resource management strengthens productivity through engagement, innovation, and environmentally responsible behavior. Madero-Gómez *et al.,* [29] systematically confirm the positive impact of sustainable practices on well-being and the environment, while Sypniewska *et al.,* [30] highlight that sustainable human resource management increases engagement and satisfaction, thereby enhancing productivity. These studies provide a basis for defining sustainable productivity as a multidimensional construct that includes operational efficiency, employee well-being, and long-term stability.

The previously mentioned studies confirm that sustainable productivity should not be reduced solely to short-term operational efficiency but must include the preservation of employee well-being and long-term organizational stability, which represents the evaluation framework of this paper. However, the literature review does not differentiate specific AI tools nor provide a structured model that accounts for the uncertainty present in expert evaluation. Therefore, this paper applies an intuitionistic MCDM approach to rank AI tools according to their contribution to sustainable productivity, thereby providing managers with an analytical decision-making tool that balances technological efficiency and human resources.

Although there is a large body of research on artificial intelligence and organizational productivity in practice, there are certain gaps that this paper seeks to address. Previous studies have focused mainly on analyzing the impact of artificial intelligence on organizational performance, without taking into account the impact of certain categories of artificial intelligence tools on sustainable productivity. Furthermore, existing studies have not integrated operational efficiency, employee well-being, motivation, and long-term organizational sustainability to the same extent as this study. Most previous studies have used traditional analytical approaches that do not capture uncertainty and imprecision in the evaluation of criteria and alternatives. This study seeks to address these gaps by using an intuitionistic fuzzy MCDM framework based on the SWARA and MABAC methods to evaluate artificial intelligence tools in the context of sustainable workforce productivity.

3. Methodology and Research Methods

In presenting the methodology, the conceptual framework of the research with defined alternatives and criteria will first be outlined, followed by the intuitionistic approach, and finally the steps of the MCDM methods that will be used will be explained.

3.1 Conceptual framework of the research

This research includes the evaluation of six AI tools that can be used in the operational work of organizations. The tools are differentiated according to their primary function and the way they affect employee work. When selecting alternatives, care was taken to select those alternatives that represent the most common categories of AI applications currently used in practice and in organizations. The selected AI tools differ in their purpose and interaction with employees, and their application affects organizational efficiency differently. Namely, some tools are primarily oriented towards increasing operational efficiency and automation, while other AI tools are focused on supporting employees in terms of learning and collaboration, and monitoring the effects of the application. Due to their differentiation, their assessment must include an examination of the effects and contributions to sustainable productivity. The six AI tools that represent the alternatives in this research are:

i. Generative AI tools (AI-1), which are used for content generation, document analysis, idea development, and assistance in creative and analytical tasks.
ii. AI tools for task automation (AI-2), which are used for automatic data processing, document classification, and similar tasks.
iii. AI tools for decision support and analytics (AI-3), where advanced analytics, predictive modeling, business intelligence, and decision-support systems help managers and employees make informed decisions.
iv. AI tools for collaboration and work organization (AI-4), which include smart scheduling assistants, automatic task organization, project management, and workflow optimization within teams.
v. AI tools for employee learning and development (AI-5), which use personalized learning platforms, adaptive skill development systems, simulations, and AI mentors that adjust content to individual employee needs.
vi. AI tools for monitoring and performance evaluation (AI-6), where algorithmic systems are used to track work performance, analyze productivity, conduct electronic monitoring, and evaluate employees.

In order to evaluate these AI tools, eight criteria were defined that reflect the concept of sustainable productivity. The criteria are derived from the Job Demands & Resources model [5, 6, 31] and the literature on sustainable human resource management [7, 8, 23, 32]. Each criterion is defined as a benefit criterion, meaning that a higher value indicates a more desirable outcome. The criteria chosen for this study aim to encompass both the operational and sustainable aspects of organizational productivity. They are intended to reflect the direct influence of AI tools on efficiency and work quality, in addition to productivity, while also considering the sustainable implications of that influence. By selecting these criteria, a narrow view of productivity may be circumvented, allowing for the inclusion of wider objectives associated with organizational management. The criteria are presented in Table 1.

The evaluation of AI tools and the determination of the importance of criteria were conducted by nine experts (E1–E9), selected from academic staff at faculties in the Republic of Croatia, specializing in human resource management, organizational psychology, and digital transformation. Each expert evaluated the AI tools and determined the importance of the criteria using linguistic ratings ranging from very bad to very good (Table 2). The value “very bad” indicates a very low contribution of a criterion or a low level of criterion satisfaction by an alternative, while “very good” indicates a very high contribution of a criterion or a high level of satisfaction by an alternative. This design of linguistic values enables a separate assessment for each alternative according to the observed criterion by experts, thereby forming the basis for multicriteria evaluation. At the same time, it allows for determining the importance of the criteria in this evaluation.

Table 1
Criteria for the Evaluation of AI Tools

Id	Criterion	Description
C-1	Increase in individual productivity	Speed and efficiency of performing work tasks using AI tools
C-2	Work quality	Accuracy, precision, and reduction of errors in daily work
C-3	Reduction of cognitive load	Reduction of mental fatigue and cognitive stress of employees during work
C-4	Low risk of burnout	Reduction of the risk of professional burnout through the use of AI tools
C-5	Employee autonomy	Retaining or increasing employees' control over work and work pace
C-6	Engagement and motivation	The impact of AI tools on employee engagement, motivation, and job satisfaction
C-7	Skill development	Contribution of AI tools to learning, training, and acquisition of new competencies
C-8	Employee retention	Long-term positive effects on employee loyalty and intention to remain in the organization

Table 2
Linguistic Values, Labels, and Membership Functions

Linguistic Values	Label	IFNs
Very good	VGO	[0.90, 0.00]
Good	GOO	[0.75, 0.15]
Medium good	MGO	[0.60, 0.30]
Fair/medium	FME	[0.45, 0.45]
Medium bad	MBA	[0.30, 0.60]
Bad	BAD	[0.15, 0.75]
Very bad	VBA	[0.00, 0.90]

3.2 Application of the Intuitionistic Approach and MCDM Methods

In the context of evaluating AI tools and sustainable workforce productivity, MCDM methods are useful as they enable the comparison of multiple alternatives according to different, often conflicting criteria [33, 34]. However, standard MCDM approaches do not take into account uncertainty and imprecision [35], which are characteristic of expert evaluations, especially when considering long-term organizational effects. To address this limitation, this paper applies an intuitionistic approach. This approach allows, in addition to the degree of membership and non-membership, the explicit incorporation of the degree of uncertainty into the decision-making process [11, 36].

In the evaluation of criteria and alternatives, linguistic values are applied. This is a standard practice in MCDM studies [37]; however, it does not account for the uncertainty and imprecision present in expert evaluations, particularly when dealing with long-term organizational outcomes of AI implementation. To overcome this limitation, the intuitionistic approach [11] is applied, enabling the inclusion of uncertainty in expert assessments. This is done by first transforming linguistic values into intuitionistic fuzzy numbers (IFNs) using predefined fuzzy values [38]. In defining these values, the degree of membership of set A $((\mu_A(x))$ and the degree of non-membership $(v_A(x))$ are considered. The part not defined by these values represents the degree of uncertainty$\left(\pi_A(x)\right)$, which is defined as follows:

$$\pi_A(x) = 1 - \mu_A(x) - v_A(x) \tag{1}$$

In this way, by defining the degree of uncertainty$\left(\pi_A(x)\right)$, a certain portion of uncertainty is incorporated into the decision-making process. In order to use IFNs for determining research results, this approach is transformed into crisp values using the steps proposed by Işık and Adalar [12]. After transforming linguistic values into IFNs, the following steps are applied:

Step 1. Determination of the positive (τ^+) and negative ideal solution (τ^-), representing the maximum values of IFNs in terms of membership and non-membership degrees.

Step 2. Determination of distance measures. In this step, the distances from the defined positive (τ^+) and negative ideal solution (τ^-) are calculated:

$$\delta_m^+ = \sqrt{\left(\mu_{\check{A}_m} - \tau^+\right)^2 + \left(v_{\check{A}_m} - \tau^+\right)^2 + \left(\pi_{\check{A}_m} - \tau^+\right)^2} \quad (2)$$

$$\delta_m^- = \sqrt{\left(\mu_{\check{A}_m} - \tau^-\right)^2 + \left(v_{\check{A}_m} - \tau^-\right)^2 + \left(\pi_{\check{A}_m} - \tau^-\right)^2} \quad (3)$$

Step 3. Calculation of the closeness coefficient (CC), based on the distance measures calculated in the previous step:

$$CC_m = \frac{\delta_m^-}{\delta_m^+ + \delta_m^-} \quad (4)$$

The obtained CC values from this approach are used as crisp values and serve to form the decision matrix for the application of classical MCDM methods. To determine the weights of the criteria, the SWARA (Stepwise Weight Assessment Ratio Analysis) method is used, while the MABAC (Multi-Attributive Border Approximation Area Comparison) method is applied to determine the ranking of AI tools. The choice of the SWARA and MABAC methods is driven by the potential to develop a hybrid methodology that integrates the steps of both methods into a cohesive framework. In contrast to other approaches, the SWARA method does not necessitate pairwise comparisons of criteria; instead, it relies solely on ranking based on expert evaluations. This characteristic represents a significant advantage of the SWARA method over its counterparts. The MABAC method was selected from a range of criteria, as it provides consistent results irrespective of the number of alternatives or criteria involved, since this method is capable to compare alternatives concerning the boundary area of approximation. Furthermore, it does not require comparisons against ideal solutions or other alternatives, demonstrating considerable robustness. Consequently, the implementation of these methods is appropriate for the assessment of AI tools.

The SWARA method is selected because, in its original formulation by Keršulienė *et al.,* [39], the authors used the overall values of criteria to determine their weights. In this way, by applying the principles of this method, experts are not required to first rank the criteria and then determine their importance relative to the highest-ranked criterion [40]. In this application of the SWARA method, experts provide importance ratings for the criteria, which are then prepared for the application of the method's steps. The steps are as follows:

Step 1. Evaluation of the importance of criteria by experts using linguistic values (Table 2).

Step 2. Transformation of linguistic values into crisp values using the approach proposed by Işık and Adalar [12].

Step 3. Determination of average values of criteria and formation of the ranking order. In this step, average CC values for each criterion are calculated, and based on these aggregate values, the ranking of criteria is established.

Step 4. Determination of relative importance of criteria. The highest-ranked criterion is assigned a value of one (1). The values of the remaining criteria are obtained by subtracting the average value of the next-ranked criterion from the average value of the higher-ranked criterion:

$$k_j = \begin{cases} 1 \; if \; j = 1 \\ s_j + 1 \; if \; j > 1 \end{cases} \quad (5)$$

Step 6. Determination of relative q_j values, following the classical SWARA method:

$$q_j = \begin{cases} 1\ if\ j = 1 \\ \frac{q_{j-1}}{k_j}\ if\ j > 1 \end{cases} \tag{6}$$

Step 7. Calculation of criteria weights:

$$w_j = \frac{q_j}{\sum_{j=1}^{n} q_k} \tag{7}$$

These weights are used in the steps of the MABAC method; therefore, it is necessary to first determine the weights and then rank the AI tools. The MABAC method is selected because it demonstrates high accuracy and reliability in determining results [41], as the calculation is based on the determination of the border approximation area [42]. Additionally, this method shows good stability of results even when criterion weights change, providing additional reliability in decision-making [43, 44]. The fuzzy MABAC method was developed by Pamučar and Ćirović [45]. The steps of this method are as follows:

Step 1. Evaluation of AI tools using linguistic values.

Step 2. Transformation of linguistic values into crisp values using the same approach.

Step 3. Normalization of the fuzzy decision matrix:

$$r_{ij} = \left(\frac{x_{ij} - x_{j\,min}}{x_{j\,max} - x_{j\,min}}\right) \tag{8}$$

Step 4. Calculation of elements of the weighted normalized matrix:

$$v_{ij} = w_i \cdot t_{ij} + w_i \tag{9}$$

Step 5. Determination of the border approximation area (g):

$$g_j = \left(\prod_{j=1}^{m} v_{ij}\right)^{1/m} \tag{10}$$

Step 6. Calculation of the distance of alternatives from the border area:

$$Q_{ij} = v_{ij} - g_j \tag{11}$$

Step 7. Calculation of MABAC values and ranking of alternatives:

$$S_i = \sum_{j=1}^{n} Q_{ij} \tag{12}$$

3.3 Comparative and Sensitivity Analysis

To confirm the results obtained, two additional analyses will be conducted: a comparative analysis and a sensitivity analysis. The objective of the comparative analysis is to examine whether the ranking of AI tools changes when other MCDM methods are used for data ranking. To achieve this, in addition to the MABAC method, AI tools will be ranked using six additional methods: TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution), ARAS (Additive Ratio Assessment), WASPAS (Weighted Aggregated Sum Product Assessment), SAW (Simple Additive Weighting), MARCOS (Measurement of Alternatives and Ranking according to COmpromise Solution), and CRADIS (Compromise Ranking of Alternatives from Distance to Ideal Solution). All these methods use different normalization procedures compared to the MABAC method; therefore, by applying these methods, the influence of normalization on the ranking is examined. Furthermore, each of these methods has specific characteristics that distinguish them within MCDM methods. TOPSIS and SAW are among the most commonly used methods in practice, making their application a logical choice. The SAW method ranks alternatives based on weighted normalized data and is one of the simplest MCDM methods in practice. The ARAS method, unlike SAW, relies solely on the calculation of an optimal function, making it very simple. The WASPAS method uses a compromise of the results of two methods, the Weighted Sum Model (WSM) and the Weighted Product Model (WPM), which is why it is included. MARCOS and CRADIS are contemporary MCDM methods that have demonstrated significant application in practice and are therefore included in this analysis.

The sensitivity analysis aims to examine how changes in the weights of criteria affect the final ranking of alternatives [46]. This analysis can be performed in various ways [47], in this research, the initial weights obtained using the SWARA method will be used. To determine sensitivity to weight changes, the values of individual criteria weights will be reduced by 20%, 50%, and 95%, while the remaining criteria weights will be proportionally increased so that the total weight remains approximately equal to one. These percentages were selected to examine different levels of impact: a 20% reduction tests whether a small decrease affects the ranking; a 50% reduction halves the weight; and a 95% reduction assigns minimal importance to the criterion, allowing the assessment of whether it was decisive in determining the ranking of alternatives. Since one criterion is reduced three times and there are eight criteria, a total of 24 scenarios will be created and used in this sensitivity analysis. By applying these two methods, the robustness and stability of the ranking of AI tools will be determined.

4. Results

By conducting the research, nine questionnaires were collected, which serve as the basis for obtaining the results of this study. The collected questionnaires were processed, and initial decision matrices were formed, which will be used to determine the values of criteria weights and to rank the AI tools. First, the weights of the criteria will be determined, as they are necessary for ranking the alternatives.

The first step in determining the importance of criteria, and thus their weights, is the evaluation by experts of the importance of the selected criteria (Table 3). In this step, experts provide assessments using a linguistic value scale based on how important each criterion is for ranking AI tools.

Table 3
Evaluation of Criteria Importance

Expert	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8
EX-1	GOD	VGO	MGO	GOD	MGO	VGO	MGO	MGO
EX-2	MGO	MGO	FME	FME	GOD	MGO	VGO	MGO
EX-3	MGO	MBA	MGO	FME	BAD	FME	MGO	MBA
EX-4	GOD	GOD	MBA	MBA	FME	FME	BAD	FME
EX-5	VGO	GOD	VGO	VGO	VGO	VGO	VGO	VGO
EX-6	VGO	VGO	GOD	MGO	FME	GOD	GOD	MBA
EX-7	GOD	MGO	MGO	MGO	MGO	GOD	GOD	GOD
EX-8	VGO	VGO	MGO	MGO	MGO	VGO	FME	MGO
EX-9	GOD	MGO	GOD	GOD	MGO	VGO	VGO	MGO

After evaluating the importance of the criteria, the steps of the SWARA method are applied. First, linguistic values are transformed into IFNs and then into crisp values by calculating CC values. This procedure will be explained using the example of the linguistic rating “good.” First, the linguistic value “good” is transformed into an IFN using the defined membership function, resulting in the value [0.75, 0.15]. Then, the degree of uncertainty is determined, which is calculated as follows:

$$\pi_A(x) = 1 - 0.75 - 0.15 = 0.10$$

After determining the degree of uncertainty, the distance measures are calculated as follows:

$$\delta_m^+ = \sqrt{(0.75 - 0.9)^2 + (0.15 - 0)^2 + (0.10 - 0)^2} = 0.23$$

$$\delta_m^- = \sqrt{(0.75-0)^2 + (0.15-0.9)^2 + (0.10-0)^2} = 1.07$$

Finally, the CC value is calculated as follows:

$$CC_m = \frac{1.07}{0.23 + 1.07} = 0.82$$

In this way, the linguistic value "good" is transformed into a CC value of 0.82, where a certain level of uncertainty is incorporated into this value. By applying this principle, CC values are formed for all linguistic values, and a decision matrix is constructed, which serves as the basis for calculating the weights of the criteria (Table 4).

Table 4
Evaluation of the importance of criteria represented through CC values

Expert	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8
EX-1	0.820	0.927	0.662	0.820	0.662	0.927	0.662	0.662
EX-2	0.662	0.662	0.500	0.500	0.820	0.662	0.927	0.662
EX-3	0.662	0.338	0.662	0.500	0.180	0.500	0.662	0.338
EX-4	0.820	0.820	0.338	0.338	0.500	0.500	0.180	0.500
EX-5	0.927	0.820	0.927	0.927	0.927	0.927	0.927	0.927
EX-6	0.927	0.927	0.820	0.662	0.500	0.820	0.820	0.338
EX-7	0.820	0.662	0.662	0.662	0.662	0.820	0.820	0.820
EX-8	0.927	0.927	0.662	0.662	0.662	0.927	0.500	0.662
EX-9	0.820	0.662	0.820	0.820	0.662	0.927	0.927	0.662
Average	0.821	0.750	0.673	0.655	0.620	0.779	0.714	0.619
Rank	1	3	5	6	7	2	4	8

After forming the CC values for the evaluation of criteria, the average values are calculated, and the criteria are ranked based on these values. This is necessary for implementing the classical steps of the SWARA method. First, the criteria are ordered according to their ranking, and then their relative importance is determined. Criterion C-1 is assigned the value one, while the values of the remaining criteria are formed based on the difference between a higher-ranked criterion and the subsequent criterion. The steps of the SWARA method are then presented using the example of C-6. In determining the relative importance of this criterion, the calculation is performed as follows:

$$k_{C-6} = 1 + 0.821 - 0.779 = 1.042$$

Using this principle, the relative weight values for all criteria are determined, after which the relative $q_j$values are calculated. For the highest-ranked criterion, the value one is assigned, while for the remaining criteria, this value is obtained by dividing the relative q_j value of the higher-ranked criterion by the relative weight value of that criterion. In the selected example, this is calculated as follows:

$$q_{C-6} = \frac{1.000}{1{,}042} = 0.960$$

After determining the relative q_j values, these values are summed, and each individual $q_j$value is divided by this sum to obtain the final criteria weights. For the selected criterion, this is calculated as follows:

$$w_{C-6} = \frac{0.960}{7.149} = 0.134$$

Based on the obtained values of criteria weights using the SWARA method, the results (Table 5) show that the most important criterion is C-1 – Increase in individual productivity, followed by C-6 – Engagement and motivation, while the least important criterion according to these evaluations is C-8 – Employee retention.

Table 5
Steps and Results of Criteria Importance Based on the SWARA Method

	k_j	q_j	w_j
C-1	1.000	1.000	0.140
C-6	1.042	0.960	0.134
C-2	1.029	0.933	0.130
C-7	1.036	0.901	0.126
C-3	1.041	0.865	0.121
C-4	1.018	0.849	0.119
C-5	1.035	0.821	0.115
C-8	1.001	0.820	0.115
		7.149	

After determining the criteria weights, the next step is the ranking of AI tools. This ranking is performed using the steps of the MABAC method. The procedure is similar to determining the importance of criteria, except that in this step experts evaluate the extent to which each AI tool satisfies the defined research objectives, using the same linguistic ratings. By applying the defined steps from the methodology, the first step in ranking AI tools is the formation of the decision matrix based on expert evaluations in the form of linguistic values (Table 6).

Table 6
Individual Decision Matrices with Expert Evaluations

EX-1	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8
AI-1	GOD	MGO	MGO	MGO	GOD	MGO	GOD	MGO
AI-2	VGO	GOD	GOD	GOD	MGO	GOD	GOD	GOD
AI-3	MGO	GOD	MGO	GOD	GOD	MGO	MGO	GOD
AI-4	MGO	MGO	GOD	MGO	GOD	MGO	MGO	FME
AI-5	VGO	GOD	VGO	VGO	GOD	VGO	GOD	VGO
AI-6	MGO	MGO	FME	MGO	GOD	MGO	FME	MGO
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
EX-9	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8
AI-1	MGO	FME	GOD	FME	MGO	MGO	MGO	FME
AI-2	MGO	MGO	GOD	FME	MGO	MGO	GOD	MGO
AI-3	VGO	VGO	FME	FME	GOD	GOD	GOD	MGO
AI-4	MBA	MBA	MBA	FME	MBA	FME	FME	FME
AI-5	MGO	FME	FME	MGO	MGO	GOD	FME	MGO
AI-6	FME	GOD	MBA	MGO	MGO	MGO	FME	FME

The procedure for transforming these linguistic values into crisp values is the same as in the formation of criteria weights and will not be presented again. After forming the CC values of these evaluations, average values are calculated and an aggregated decision matrix is constructed, which serves as the basis for ranking using the MABAC method. Since the MABAC method is widely used in practice, its steps will not be explained in detail. Once the decision matrix is formed, the data are first normalized (expression 8), followed by the calculation of weighted normalized values using the criteria weights (expression 9). The next step is determining the border approximation area (g), which represents the geometric mean for each criterion (expression 10). Then, the distances of alternatives from the border approximation area are calculated (expression 11), and based on the sum of these distances, the final MABAC values are obtained (expression 12).

The results of applying the MABAC method based on expert evaluations (Table 7) show that the highest-ranked AI tool is AI-5 – AI tools for employee learning and development, followed by AI-3 – AI tools for decision support and analytics, while the lowest-ranked AI tool is AI-6 – AI tools for monitoring and performance evaluation. The obtained results will be further examined through additional analyses.

Table 7
Distances of Alternatives from the Border Approximation Area and Ranking of Alternatives

Alt.	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	S_i	Rank
AI-1	0.052	-0.019	0.042	-0.007	0.044	0.007	0.012	-0.030	0.103	3
AI-2	0.064	-0.034	0.042	0.017	-0.032	-0.053	-0.005	-0.022	-0.022	4
AI-3	-0.010	0.025	0.017	0.017	0.044	-0.023	0.029	0.012	0.110	2
AI-4	-0.049	-0.048	-0.001	0.041	-0.032	0.022	-0.039	0.003	-0.103	5
AI-5	0.064	0.082	0.008	0.041	0.064	0.081	0.079	0.085	0.503	1
AI-6	-0.076	0.025	-0.079	-0.078	-0.051	-0.008	-0.047	-0.022	-0.336	6

The comparative analysis is the first additional analysis conducted in this research. The results obtained using the MABAC method are compared with the results of the other applied methods [48] in this analysis. The results show that there is no difference in the rankings obtained using other methods (Figure 1). Based on this, it can be concluded that there are clear differences among the AI tools, and the application of other methods did not affect the ranking order. These results confirm that the MABAC method provides stable and reliable results, and this method can be considered suitable for future studies of similar decision-making problems.

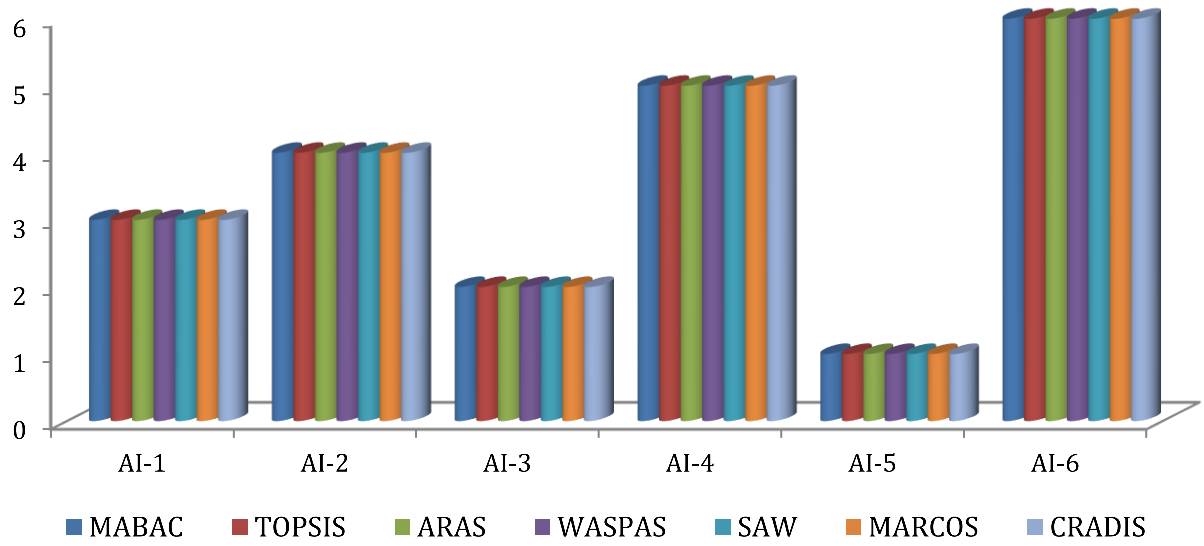

Fig. 1. Results of the Comparative Analysis

A sensitivity analysis is conducted following the comparative analysis. As described in the methodology, 24 scenarios were created, and the results indicate certain changes in the ranking of AI tools (Figure 2). The results of this analysis show that in one scenario (S3), there was a change in the ranking of alternatives AI-2 and AI-4, where AI-4 achieved a better ranking. This occurred because, for criterion C-1, AI-2 had better evaluations than AI-4; thus, reducing the importance of this criterion by 95% led to a change in their ranking. For AI-4 to outperform AI-2, it is necessary to improve its characteristics, particularly in meeting the requirements of criterion C-1. Other changes occurred between AI-3 and AI-1 in ten scenarios. This indicates that the results for these two AI tools were approximately equal, and changes in criteria weights led to changes in their ranking. For one of these tools to outperform the other, improvements must be made in the criteria where ranking changes occurred, which is particularly important for AI-1.

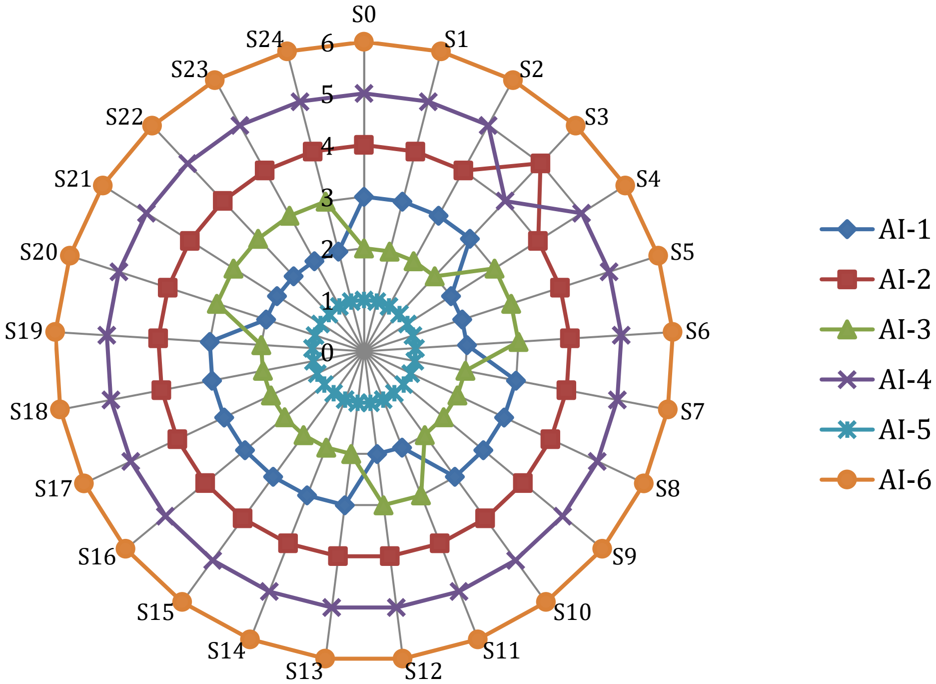

Fig. 2. Results of the Sensitivity Analysis Scenarios

5. Discussion

The research conducted provides significant insight into the evaluation of AI tools from the perspective of sustainable productivity. The study incorporates uncertainty and imprecision that are present in expert assessments through the methodological framework, particularly when evaluating long-term organizational outcomes. This was enabled through the application of the intuitionistic approach, using the SWARA and MABAC methods. To apply this approach, IFNs were transformed in accordance with the approach developed by Işık and Adalar [12]. In this way, IFNs were converted into crisp values, which served as the basis for calculating criteria weights and ranking AI tools using classical MCDM methods [49]. To ensure appropriate evaluation, nine experts from the academic community, specializing in human resource management and organizational culture, were engaged to assess the importance of criteria and AI tools.

The implementation of an intuitionistic fuzzy approach in this study was crucial, as the evaluation of AI tools relied exclusively on the subjective assessments of the experts. Nevertheless, these specialists could not accurately determine the impact of AI tools on organizational efficiency; rather, they can only formulate hypotheses. Consequently, the evaluation of this uncertainty is imprecise, as experts cannot furnish entirely accurate data [50]. Thus, employing an intuitionistic fuzzy approach enables the expression of degrees of belonging and non-belonging, which in turn facilitates the assessment of uncertainty. When defining the degree of uncertainty, care was taken that this degree remained consistent across all assessments, given that uncertainty is always present, making it challenging to ascertain the level of uncertainty. This aspect is particularly significant in the context of AI tool application, as determining the long-term impacts of these tools is inherently difficult. Therefore, the intuitionistic fuzzy approach enhances the reliability of the evaluation process and establishes a solid foundation for making informed decisions regarding the selection of AI tools.

In the analysis of the selected criteria, the most important were C-1 – Increase in individual productivity, followed by C-6 – Engagement and motivation. These results indicate that experts perceive operational efficiency as the primary objective of using AI tools in organizations and emphasize the key role of employee motivation in the use of these tools. These findings confirm the assumptions of the Job Demands & Resources model [5, 6], where technology is viewed as a resource that reduces job demands rather than as a generator of new demands in organizations. Technology, especially AI tools, should serve to facilitate organizational operations and enable employees to perform tasks more easily. However, this research shows that the least important criterion, according to expert opinion, is C-8 – Employee retention. This does not mean that experts consider this criterion unimportant, but rather that it is a consequence of effective management of other organizational dimensions. If employees are motivated and their work is facilitated through the introduction of AI tools, they will be satisfied with the organization and remain employed there. Therefore, it is necessary to provide comprehensive support to employees in order to retain them, rather than focusing solely on retention itself [51]. The application of these tools should ensure increased productivity, as well as the development of employee skills and knowledge, while simultaneously working on employee satisfaction to enhance loyalty and retention, since employees represent a key organizational resource.

The evaluation of AI tools produced results showing that AI-5 – AI tools for employee learning and development is the most effective tool for increasing organizational efficiency through improved employee productivity. These results indicate that this tool dominates over others by enhancing productivity through the development of competencies and knowledge, thereby contributing to skill development. Such findings are consistent with the concept of human-centered AI [24], according to which technological solutions should contribute to long-term organizational well-being. Additionally, investment in employees is necessary to improve human resources within organizations [52], which can be achieved through the use of personalized platforms where AI tools provide individualized support and tailor the learning process to each employee. High evaluations were also assigned to AI-3 – AI tools for decision support and analytics, where experts recognized its advantage in enabling higher-quality work based on informed decision-making. However, the application of this tool must also take into account employee input within the organization [53]. As shown by the sensitivity analysis, in certain scenarios (ten scenarios), this tool demonstrated weaker performance compared to AI-1 – Generative AI tools, indicating that this tool also plays a significant role in increasing productivity and efficiency in organizations.

The lowest results were achieved by AI-6 – AI tools for monitoring and performance evaluation. This result is consistent with criticisms of algorithmic surveillance [3], where electronic monitoring, although providing useful information, has negative effects on employees by increasing workload and the risk of burnout. Experts therefore assessed that sustainable productivity cannot be based on control [54]. These findings were confirmed through comparative and sensitivity analyses, demonstrating that the results are consistent and that difference arise solely from the characteristics of individual AI tools [55, 56].

5.1 Managerial Implications

The value of this research lies in providing a structured analytical tool for decision-making regarding the implementation of AI technologies in everyday business operations [57]. The results indicate that priority for managers and decision-makers should be given to AI tools for employee learning and development (AI-5). These tools simultaneously improve key drivers of sustainable productivity by enhancing individual efficiency, engagement, and competency development. Their application improves employee performance while encouraging continuous learning, which is essential for organizational improvement. At the same time, these tools directly contribute to long-term employee well-being, reducing employee turnover and the risk of burnout.

Decision-support tools (AI-3) and generative AI (AI-1) also showed strong results, indicating that they can contribute to maximizing benefits and productivity while minimizing the risk of employee concerns about being replaced by AI. Therefore, these tools should be introduced gradually, with the aim of supporting employees rather than replacing them. The primary purpose of these technologies is to provide support and access to large amounts of information, with a focus on developing employee knowledge and skills. Accordingly, the goal of managers should not be to replace employees but to support their work while reducing the risk of burnout. Managers should design the implementation of AI tools gradually and transparently and use feedback mechanisms for control, rather than relying on monitoring tools, as indicated by this research.

The results related to criteria provide managers with clear guidance, emphasizing the need to focus on monitoring the efficiency of task execution while also incorporating indicators of employee engagement and motivation. Applying AI tools in this way can increase employee satisfaction, reduce turnover, and retain human resources within organizations as one of their most important assets.

5.2 Limitations and Directions for Future Research

This research has certain limitations that should be considered when interpreting the results. First, the study is limited by the involvement of nine experts from the academic community in the Republic of Croatia. Although these experts possess relevant knowledge, including a larger number of experts would contribute to greater diversity in responses. Additionally, future research should be directed toward specific sectors, as not all AI tools have the same effects due to organizational differences. Furthermore, the criteria and alternatives included in this study may also be considered limitations. While other criteria and alternatives could be used, no study can encompass all possible variables, which is an inherent limitation in MCDM approaches. This research could also have examined the synergy of multiple AI tools rather than analyzing them individually, as the combined effects of multiple tools may exceed those of a single tool.

The research is based exclusively on qualitative indicators and does not include quantitative data that could be obtained through direct measurement of employee productivity. The absence of real data can therefore be considered an additional limitation. The use of linguistic evaluations by experts may also introduce challenges, as it can be difficult to distinguish between categories such as “good” and “very good.” However, using numerical ratings (e.g., from 1 to 10 with decimal values) could complicate the evaluation process, as it is difficult to precisely determine the importance of criteria or the level of satisfaction of AI tools due to the subjective nature of the assessment. For this reason, the intuitionistic approach was applied to incorporate uncertainty and imprecision into decision-making. Nevertheless, the use of this approach can also be viewed as a limitation, as alternative methods could have been applied. The challenge with MCDM-based decision-making lies in the wide variety of available approaches and methods, making it difficult to determine which combination yields the most accurate results. Therefore, additional analyses are conducted to validate the findings. Furthermore, the use of CC coefficients introduces a certain level of defuzzification information entropy, which may also be considered a limitation. In general, any methodological choice can be viewed as a limitation, as alternative approaches could always be considered. For this reason, directions for future research are provided to further improve the field.

Future research should aim to address some of these limitations. Studies could be directed toward managers and organizations rather than relying solely on academic experts, as managers have direct experience with the implementation of AI tools. The number of criteria could be expanded or grouped to allow for a more systematic evaluation process. Additionally, new AI tools could be included to assess whether they yield better results. From a methodological perspective, future studies could apply other extensions of fuzzy sets, such as Pythagorean or spherical fuzzy numbers, to allow for a broader representation of uncertainty and imprecision. Dynamic MCDM models could also be used to simulate the implementation of AI tools and their potential outcomes in organizations. Furthermore, incorporating quantitative data could reduce subjectivity in decision-making.

6. Conclusion

The aim of this research was to provide a structured response to the challenges of evaluating AI tools in the context of sustainable productivity, with particular attention to ensuring that short-term operational efficiency does not compromise long-term employee well-being. To achieve this, a multidimensional decision-making model was developed, incorporating eight criteria and six AI tools. By applying the intuitionistic approach with the SWARA and MABAC methods, a methodological framework was established that integrates uncertainty and imprecision into the decision-making process. The results showed that the key criteria for evaluating AI tools are focused on increasing productivity and employee motivation, ensuring that employees are satisfied with the organization and become loyal. Only in this way can sustainable productivity be developed while retaining human resources through continuous investment.

The results also indicate that AI tools should be oriented toward employees, supporting their learning and development in order to build human resources capable of responding to market changes driven by AI-based technologies. Furthermore, the research shows that algorithmic monitoring and control based on AI do not produce favorable results compared to other AI tools, leading to their lowest ranking. This highlights the importance of investing in employees by providing favorable conditions for growth and enabling them to use acquired knowledge for the benefit of the organization, thereby achieving sustainable productivity that supports organizational development.

A key challenge in implementing modern technologies is employee resistance, often driven by concerns that AI may reduce their role or make them redundant. Therefore, it is essential to balance technological progress with social sustainability, ensuring that technological advancement does not undermine the social dimension within organizations.

Funding
This research received no external funding.

Data Availability Statement
The authors confirm that the data supporting the findings of this study are available within the article.

Conflicts of Interest
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement
Funded by the European Union - NextGenerationEU: Contemporary Challenges of the Labour Market and Human Resource Management in the European Union (LABOR-EU), IP-UNIZD-2025-27000. The views and opinions expressed are those of the authors only and do not necessarily reflect the official views of the European Union or the European Commission. Neither the European Union nor the European Commission can be held responsible for them.

References
[1] Brynjolfsson, E., Rock, D., & Syverson, C. (2017). *Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics* (Working Paper 24001). National Bureau of Economic Research. https://doi.org/10.3386/w24001
[2] Brynjolfsson, E., Li, D., & Raymond, L. (2023). *Generative AI at Work* (Working Paper 31161). National Bureau of Economic Research. https://doi.org/10.3386/w31161
[3] Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals*, 14(1), 366–410. https://doi.org/10.5465/annals.2018.0174
[4] Meijerink, J., & Bondarouk, T. (2023). The duality of algorithmic management: Toward a research agenda on HRM algorithms, autonomy and value creation. *Human Resource Management Review*, 33(1), 100876. https://doi.org/10.1016/j.hrmr.2021.100876
[5] Demerouti, E., Bakker, A. B., Nachreiner, F., & Schaufeli, W. B. (2001). The job Demands & Resources model of burnout. *Journal of Applied Psychology*, 86(3), 499-512. https://doi.org/10.1037/0021-9010.86.3.499
[6] Bakker, A. B., & Demerouti, E. (2007). The Job Demands-Resources model: state of the art. *Journal of Managerial Psychology*, 22(3), 309–328. https://doi.org/10.1108/02683940710733115
[7] Mitrovic Veljkovic, S., Djakovic Radojicic, I., Nesic Tomasevic, A., Subotic, M., Nikolic, D., & Dudic, B. (2026). Decision-Making Style of Managers in the Public Sector: Is There a Possibility for Improvement? *International Journal of Economic Sciences*, 15(1), 386-405. https://doi.org/10.31181/ijes1512026283
[8] Kramar, R. (2014). Beyond strategic human resource management: is sustainable human resource management the next approach? *The International Journal of Human Resource Management*, 25(8), 1069–1089. https://doi.org/10.1080/09585192.2013.816863
[9] Pezeshgi, A., Abarghoei, M. V., Naeimi, M., & Family, Q. (2026). Trusting the Machine: How Consumer Trust in Artificial Intelligence Shapes Future Adoption Intentions. *Management Science Advances*, 3(1), 237-245. https://doi.org/10.31181/msa31202640
[10] Özekenci, E. K. (2025). A Multi-Criteria Framework for Economic Decision Support in Urban Sustainability: Comparative Insights from European Cities. *International Journal of Economic Sciences*, 14(1), 162-181. https://doi.org/10.31181/ijes1412025188
[11] Atanassov, K. T. (1986). Intuitionistic fuzzy sets. *Fuzzy Sets and Systems*, 20(1), 87–96. https://doi.org/10.1016/s0165-0114(86)80034-3
[12] Işık, Ö., & Adalar, İ. (2025). A multi-criteria sustainability performance assessment based on the extended CRADIS method under intuitionistic fuzzy environment: A case study of Turkish non-life insurers. *Neural Computing & Applications*, 37(5), 3317–3342. https://doi.org/10.1007/s00521-024-10803-0
[13] Tešić, D. (2025). A Machine Learning and Multi-Criteria Decision-Making Framework for Student Grade Prediction. *Smart Multi-Criteria Analytics and Reasoning Technologies*, 1(1), 22-32. https://doi.org/10.65069/smart1120253
[14] Cherradi, M., & El Haddadi, A. (2024). Comparative Analysis of Machine Learning Algorithms for Sentiment Analysis in Film Reviews. *Acadlore Transactions on AI and Machine Learning*, 3(3), 137-147. https://doi.org/10.56578/ataiml030301
[15] Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *The Journal of Economic Perspectives*, 29(3), 3–30. https://doi.org/10.1257/jep.29.3.3
[16] Acemoglu, D., & Restrepo, P. (2018). *Artificial Intelligence, Automation and Work* (Working Paper 24196). National Bureau of Economic Research. https://doi.org/10.3386/w24196
[17] Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review*, 46(1), 192–210. https://doi.org/10.5465/amr.2018.0072
[18] Ball, K. (2010). Workplace surveillance: an overview. *Labor History*, 51(1), 87–106. https://doi.org/10.1080/00236561003654776
[19] Ravid, D. M., Tomczak, D. L., White, J. C., & Behrend, T. S. (2020). EPM 20/20: A review, framework, and research agenda for electronic performance monitoring. *Journal of Management*, 46(1), 100–126. https://doi.org/10.1177/0149206319869435

[20] Schaufeli, W. B., Salanova, M., González-Romá, V., & Bakker, A. B. (2002). The measurement of engagement and burnout: A two sample confirmatory factor analytic approach. *Journal of Happiness Studies*, 3(1), 71–92. https://doi.org/10.1023/A:1015630930326

[21] Tarafdar, M., Cooper, C. L., & Stich, J.-F. (2019). The technostress trifecta - techno eustress, techno distress and design: Theoretical directions and an agenda for research. *Information Systems Journal*, 29(1), 6–42. https://doi.org/10.1111/isj.12169

[22] Docherty, P., Kira, M., & Shani, A. B. (2009). *Creating Sustainable Work Systems: Developing Social Sustainability*. Routledge.

[23] Mariappanadar, S. (2020). *Sustainable Human Resource Management: Strategies, Practices and Challenges*. Red Globe Press.

[24] Shneiderman, B. (2022). *Human-Centered AI*. Oxford University Press.

[25] Sheeran, Z., Sutton, A., & Cooper-Thomas, H. D. (2025). Environmental sustainability and the happy-productive worker: examining the impact on employee well-being and work performance in educational institutions. *International Journal of Educational Management*, 39(2), 469–487. https://doi.org/10.1108/ijem-11-2024-0704

[26] Ramgolam, G., Ramphul, N., & Chittoo, H. (2025). The role of sustainable human resource management practices to achieve sustainable employee performance – literature review and future research directions. *The Learning Organization*, 32(6), 885–903. https://doi.org/10.1108/tlo-01-2025-0014

[27] Jiang, Y., Jamil, S., Zaman, S. I., & Fatima, S. A. (2024). Elevating organizational effectiveness: synthesizing human resource management with sustainable performance alignment. *Journal of Organizational Effectiveness: People and Performance*, 11(2), 392–447. https://doi.org/10.1108/joepp-03-2023-0111

[28] Islam, M. F., Al Masud, A., Emon, M., Shuvro, R. A., Jony, M. T. I., & Akter, T. (2025). Integrating green HRM for productivity and sustainability: green innovation, engagement and pro-environmental behavior as key mediators. *Future Business Journal*, 11(1), 24. https://doi.org/10.1186/s43093-025-00433-w

[29] Madero-Gómez, S. M., Rubio Leal, Y. L., Olivas-Luján, M., & Yusliza, M. Y. (2023). Companies Could Benefit When They Focus on Employee Wellbeing and the Environment: A Systematic Review of Sustainable Human Resource Management. *Sustainability*, 15(6), 5435. https://doi.org/10.3390/su15065435

[30] Sypniewska, B., Baran, M., & Kłos, M. (2023). Work engagement and employee satisfaction in the practice of sustainable human resource management – based on the study of Polish employees. *International Entrepreneurship and Management Journal*, 19(3), 1069–1100. https://doi.org/10.1007/s11365-023-00834-9

[31] Khlud, V. (2026). Governing Fair Algorithmic Hiring Under the EU AI Act: A Multi-Layer Decision Architecture for High-Risk Recruitment Systems. *Applied Decision Analytics*, 2(1), 271-282.

[32] Ilinca Fron, M., & Fleseriu, C. (2025). AI versus Human Content Creation on Instagram: Engagement Outcomes and Consumer Perceptions. *Oeconomica Jadertina*, 15(2), 19-47. https://doi.org/10.15291/oec.4845

[33] Petrović, N., Jovanović, V., Marković, S., Marinković, D., & Petrović, M. (2024). Multicriteria sustainability assessment of transport modes: A European Union case study for 2020. *Journal of Green Economy and Low-Carbon Development*, 3(1), 36–44. https://doi.org/10.56578/jgelcd030104

[34] Chabok, S. H., & Tešić, D. (2024). Comprehensive strategic planning for construction companies using fuzzy MADM techniques. *Journal of Operational and Strategic Analytics*, 2(4), 235–253. https://doi.org/10.56578/josa020403

[35] Katrancı, A., Kundakcı, N., & Arman, K. (2026). Fuzzy SIWEC and Fuzzy RAWEC Methods for Sustainable Waste Disposal Technology Selection. *Spectrum of Operational Research*, 3(1), 87-102. https://doi.org/10.31181/sor31202633

[36] Ali, A., Ullah, K., & Hussain, A. (2023). An approach to multi-attribute decision-making based on intuitionistic fuzzy soft information and Aczel-Alsina operational laws. *Journal of Decision Analytics and Intelligent Computing*, 3(1), 80–89. https://doi.org/10.31181/jdaic10006062023a

[37] Petrović, I. B., & Petrović, M. D. (2025). Optimization of the short-range surface-to-air artillery-missile system design process using the hybridized triangular IT2FS-DEMATEL-MABAC approach. *Vojnotehnički glasnik/Military Technical Courier*, 73(3), 826-855. https://doi.org/10.5937/vojtehg73-57246

[38] Shahin, V., Alimohammadlou, M., & Pamucar, D. (2026). An Interval-Valued Circular Intuitionistic Fuzzy MARCOS Method for Renewable Energy Source Selection. *Spectrum of Decision Making and Applications*, 3(1), 243-268. https://doi.org/10.31181/sdmap31202645

[39] Keršulienė, V., Zavadskas, E. K., & Turskis, Z. (2010). Selection of rational dispute resolution method by applying new Step-Wise Weight Assessment Ratio Analysis (SWARA). *Journal of Business Economics and Management*, 11(2), 243–258. https://doi.org/10.3846/jbem.2010.12

[40] Li, D., Rong, Y., Zhang, B., & Simic, V. (2026). Assessing digital transformation capability evaluation of logistics enterprises utilizing spherical fuzzy alternative ranking order method accounting for two-step normalization approach. *Facta Universitatis, Series: Mechanical Engineering*, 24(1), 089-116. https://doi.org/10.22190/FUME250615003L

[41] Yalçın, G. C., Özyürek, H., & Dişçi, C. (2026). Benchmarking the Financial Performance of the Corporate Governance Index under Borsa Istanbul Companies Using SITDE and MABAC Framework. *Journal of Contemporary Decision Science*, 2(1), 169-193.

[42] Kara, K., Yalçın, G. C., & Özekenci, E. K. (2025). Measuring Logistics Performance in Emerging Economies: Insights from the SITDE–MABAC Method. *Journal of Operational and Strategic Analytics*, 3(4), 211-223. https://doi.org/10.56578/josa030401

[43] Sharma, S., & Singh, S. (2025). Single – Valued Neutrosophic Yager Power Aggregation Operators and Its Application to MCDM. *Yugoslav Journal of Operations Research*, 35(4), 837–856. https://doi.org/10.2298/YJOR240715004S

[44] Vahabzadeh, S., Haghshenas, S., Ghoushchi, S., Guido, G., Simic, V., & Marinkovic, D. (2025). A new framework for risk assessment of road transportation of hazardous substances. *Facta Universitatis, Series: Mechanical Engineering*, 23(3), 479-509. https://doi.org/10.22190/FUME240801007V

[45] Pamučar, D., & Ćirović, G. (2015). The selection of transport and handling resources in logistics centers using Multi-Attributive Border Approximation area Comparison (MABAC). *Expert Systems with Applications*, 42(6), 3016-3028. https://doi.org/10.1016/j.eswa.2014.11.057

[46] Ergün, M. (2025). Strategic Assessment of Port Logistics Information Systems Using Fuzzy FUCOM–Fuzzy RAWEC: A Case from the Black Sea Region. *Journal of Organizations, Technology and Entrepreneurship*, 3(1), 36-55. https://doi.org/10.56578/jote030103

[47] Yalçın, G. C., Kara, K., Gürol, P., & Babič, M. (2025). A Fermatean Fuzzy MCDM Framework for Green Port Transformation and Heavy-Duty Forklift Selection. *Journal of Engineering Management and Systems Engineering*, 4(4), 269-283. https://doi.org/10.56578/jemse040404

[48] Saeed, M., Inam, U. H. H., Ali, M., & Mustafa, M. (2026). A Robust Algorithmic Framework for the Evaluation of World Happiness Ranking Based on Q Rung Orthopair Triangular Fuzzy Neutrosophic Set With Possibility Setting (PQ-RTFNS). *Yugoslav Journal of Operations Research*, 36(1). https://doi.org/10.2298/YJOR240718017S

[49] Mishra, A. R., & Rani, P. (2025). Evaluating and Prioritizing Blockchain Networks using Intuitionistic Fuzzy Multi-Criteria Decision-Making Method. *Spectrum of Mechanical Engineering and Operational Research*, 2(1), 78-92. https://doi.org/10.31181/smeor21202527

[50] Bakary, S., Bouraima, M. B., & Badi, I. (2026). A Multi-Criteria-Decision Making Methodology to Prioritizing Telemedicine Expansion Opportunities. *Journal of Contemporary Decision Science*, 2(1), 55-63.

[51] Obeidat, A. M., Khaddam, A. A., Alzghoul, A., Al Afeshat, M. T. M., & Al Ghizzawi, M. (2026). How Business Intelligence Shapes Service Innovation: Knowledge Sharing as a Mediator and Culture as a Moderator in the Jordanian Context. *Economics - Innovative and Economic Research Journal*, 14(1), 391-411. https://doi.org/10.2478/eoik-2026-0019

[52] Jemmali, S., Sadraoui, T., & Azouzi, M. A. (2026). CEO Emotional Intelligence Level, Creativity, Innovation and Economic Growth. *Economics - Innovative and Economic Research Journal*, 14(1), 413-439. https://doi.org/10.2478/eoik-2026-0020

[53] Botunac, I. (2025). Implementacija višeagentnog sustava umjetne inteligencije za donošenje financijskih trgovačkih odluka. *Oeconomica Jadertina*, 15(2), 90-115. https://doi.org/10.15291/oec.4863

[54] Sarkar, A., & Goswami, S. S. (2026). A Review of the Application of MCDM Methods in Business Analytics. *Applied Decision Analytics*, 2(1), 150-180. https://doi.org/10.66972/ada21202614

[55] Yürüyen, A. A., & Ulutaş, A. (2024). Assessing the urban competitiveness of European cities using LOPCOW-RAWEC methodologies. *International Journal of Knowledge and Innovation Studies*, 2(3), 179–189. https://doi.org/10.56578/ijkis020305

[56] Mitrović, D., Demir, G., Badi, I., & Bouraima, M. B. (2025). Balancing Efficiency and Risk in Public Sector Artificial Intelligence with Data Envelopment Analysis and Portfolio Approaches. *Applied Decision Analytics*, 1(1), 15-35. https://doi.org/10.66972/ada1120254

[57] Nedeljković, M., Đokić, M., & Ćosić, M. (2026). Selection of Robots in Precision Agriculture Using Multi-Criteria Decision-Making Methods. *Smart Multi-Criteria Analytics and Reasoning Technologies*, 2(1), 1-13. https://doi.org/10.65069/smart2120265