
EVALUATION OF CRITERIA FOR THE DIGITALIZATION OF AGRICULTURAL MACHINERY

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ARTICLE INFO

Original Article

Received: 02 April 2026

Accepted: 15 May 2026

doi:10.59267/ekoPolj2602453N

UDC 005.311:[004:631.3

Keywords:

Digitalization, Agricultural Machinery, Multi-Criteria Decision Making, SiWeC method.

JEL: Q10, Q16, C1

ABSTRACT

In the paper, using the multi-criteria decision-making method SiWeC, the digitization criteria were evaluated on the example of medium- and heavy-duty tractors. A fuzzy variant of the multi-criteria decision-making method was used in order to obtain as precise assessment of the given ten qualitative criteria as possible. The results show that, according to the expert evaluation, the technical criterion "Precision of operations" gained the most importance, while immediately after them in importance were the criteria related to the level of work automation and digital connectivity. The results show important implications for decision makers, technology producers and the shaping of agricultural policy. In the future, the model needs to be expanded with impact criteria, and the number of decision-makers who would give a practical contribution, as well as a base for further development of the applied research method, should be increased.

Introduction

Digitization of agricultural equipment is a important segment of the agricultural revolution. This approach includes the introduction of advanced information and communication technologies into automated processes in food production. The goal is not only to replace the human workforce, but also to achieve an improved level of efficiency, precision and sustainability (Kiktev et al., 2025; Pantović et al., 2026). Classical mechanized methods, although effective at the macro level, often result in the waste of resources such as seeds and fertilizers, with heterogeneous yield results due to the inability to adapt to spatial

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variations within the plot (Wang et al., 2025; Janković & Golubović, 2025; Zhang, 2023; Luković et al., 2026). Digitization is currently emerging as a solution to these challenges, enabling a shift from standardized processing to flexible, analysis-driven application of data. Modern agriculture faces a contradiction: it is necessary to significantly improve food production in order to feed the growing global population, while at the same time reducing the harmful effects on the environment and mitigating the effects of climate change, with a constant shortage of labor in rural areas. (Padhiary et al., 2024; Vujanić et al., 2026; Wang et al., 2025) In this context, the digitization of agricultural machinery ceases to be only a technological advance, and becomes an economic and environmental necessity.

Multi-criteria decision-making methods play a major role in the evaluation of digitalization criteria. An expert assessment of pre-set criteria provides a rational insight into their weight (importance), which enables their development or eliminates negative influence. Accordingly, the subject of the research is the identification and assessment of important criteria that influence the digitization process on the example of medium-heavy and heavy tractors, with special emphasis on technological, operational and economic aspects. The analysis includes the use of the fuzzy multi-criteria decision-making method SiWeC (*Simple Weight Calculation*) in order to quantify the importance of individual criteria and clarify their influence on the decision-making process in modern agricultural systems.

The main goal of the work is the development and implementation of an integrated model for evaluating the criteria of digitization of medium-heavy and heavy tractors using the fuzzy multi-criteria decision-making method. Specific objectives include: determination of the relative weights of criteria using the fuzzy SiWeC approach, validation and comparison of results using other methods of multi-criteria analysis, analysis of model consistency and robustness using correlation, as well as identification of key factors that have the greatest impact on digital transformation in agricultural mechanization.

Accordingly, the main hypothesis in the paper would be that the application of fuzzy multi-criteria decision-making methods enables reliable determination of the relative weights of tractor digitization criteria, whereby technological criteria have a dominant influence.

Literature review

In their previous works and studies, many researchers have dealt with the application of multi-criteria decision-making methods when the subject was digitization in agriculture and agribusiness. Thus Albahri et al. (2025) in their work investigate the fusion of sensor technologies and multi-criteria decision-making methods (MCDM) in precision agriculture. The authors recognize three key application areas: sensor selection for irrigation systems, sensor selection for crop monitoring, and sensor selection for machine control. The paper contains 47 references and offers a comprehensive overview of the methods used, including AHP, ANP, TOPSIS, VIKOR and PROMETHEE method.

Nanje et al. (2024) used a multi-criteria approach to evaluate the suitability of areas for the use of potato harvesters in Kenya. The research applied the AHP method to

determine the weights of the criteria (soil, climate, relief, infrastructure) and GIS for spatial analysis. Kizielewicz et al. (2025) created a comprehensive decision-making framework based on MCDM methods for the evaluation of intelligent sensors for drones (UAVs) in the field of precision agriculture. The framework integrates objective weight estimation methods (Standard Deviation, Entropy, CRITIC and MEREC) with four MCDM ranking techniques, including the new COCOCOMET (COMbined COMpromise solution with Characteristic Objects METHod) method. The survey included 11 sensor options and 9 evaluation criteria. Kenarsari et al. (2024) used the integration of AHP and GRA methods to select a sustainable combination of machinery in rice production. The research included economic (costs, operating costs, durability), social (safety, ergonomics, ease of handling) and environmental (fuel consumption, gas emissions, impact on the earth) criteria. Weight criteria were determined using the Delphi method and partial comparisons. The authors point out that hybrid methods serve as a powerful instrument for solving questions that include qualitative and quantitative criteria. El-Sayed et al. (2024) proposed a combination of AHP method with machine learning (hierarchical agglomerative clustering) to select a sustainable tractor for small farms in Egypt. The initially identified nine criteria (price, power, fuel consumption, maintenance costs, weight, working life, safety, ergonomics and environmental performance) were summarized into three basic criteria, namely: price, power and maintenance costs.

In addition to everything, many studies also confirm the successful application of the fuzzy variant of multi-criteria methods when it comes to the use of digitalization in agricultural machinery. Sarkar et al. (2024) used a fuzzy AHP approach to evaluate and select tractors for small farms in Bangladesh. The research included 5 options and 12 parameters divided into three groups: technical (engine power, working width, weight, payload), economic (price, fuel consumption, maintenance costs) and social (safety, ergonomics, ease of handling). Chauhan et al. (2023) created a coupled fuzzy AHP and fuzzy TOPSIS model for combine selection for wheat harvesting in India. The research included 6 different types of harvesters and 9 evaluation criteria: harvesting capacity, harvesting losses, fuel consumption, price, service costs, availability of spare parts, ease of operation, safety and environmental aspects. Fuzzy AHP is used to determine the weights of criteria, while fuzzy TOPSIS is used to classify alternatives. Büyükožkan et al. (2024) applied the fuzzy TOPSIS method for the selection of smart sensors in precision agriculture in Turkey.

The research included 8 sensor options and 7 criteria: accuracy, dependability, cost, ease of integration, energy efficiency, resistance to the external environment and compatibility with IoT platforms. Liu et al. (2024) created a fuzzy VIKOR model to select the best sensor-integrated irrigation system in China. The research included 5 irrigation systems and 11 criteria divided into technical, economic, ecological and social categories. Peci et al. (2025) created a hybrid phase model that relies on a combination of LOPCOW and MABAC methods to select the best tractor for the Myzeqe area in Albania. The survey included 15 tractors with different characteristics,

and the evaluation was performed according to seven criteria: engine power, price, fuel consumption, weight, load capacity, durability and maintenance costs. The authors were introduced to the extension phase of both methods in order to solve the uncertainty in the estimates. Kumar et al. (2023) created an integrated SWARA (Step-wise Weight Assessment Ratio Analysis) model and WASPAS (Weighted Aggregated Sum Product Assessment) model for sensor selection in precision agriculture in India. The research covered 7 sensor options and 8 criteria: accuracy, response speed, cost, power consumption, compliance, robustness, ease of calibration and availability. Fuzzy SWARA was used to define criteria weights by comparing the importance of criteria by experts, while fuzzy WASPAS was used to rank options. Nedeljković et al. (2021) select apple picking machines using the fuzzy CRITIC and MARCOS methods based on seven predetermined criteria, while Puška et al. (2025) select the most favorable from the category of electric tractors for small farms in the Semberija region of Bosnia and Herzegovina. On this occasion, the authors use the new fuzzy SiWeC-RAWEC multi-criteria decision-making method. Also, Puška et al. (2024) evaluate tractors using the fuzzy SAW method of multi-criteria analysis.

Methodology

The analysis of interested parties recognizes agricultural farms as the main actors in the process of digitalization of agricultural equipment, because they make important investment and operational decisions. These actors function in collaboration with technical experts, technology producers and institutional frameworks, which influence the availability, choice and use of digital solutions. The results show a complex decision-making system, in which direct and indirect participants jointly shape the success of digital transformation in agriculture. This work involved seven experts from the field with extensive experience in the analyzed field. (Table 1)

Table 1. Linguistic scale

1	Very-Low (V-L)	(1. 1. 2)
2	Low (L)	(1. 2. 4)
3	Medium-Low (M-L)	(2. 4. 6)
4	Medium (M)	(3. 5. 7)
5	Medium-Good (M-G)	(5. 7. 9)
6	Good (G)	(7. 9. 10)
7	Very-Good (V-G)	(9. 10. 10)

Source: Puška et al., 2024a

Before the very beginning of the evaluation, the criteria were determined, which were once again agreed upon by the engaged experts on the basis of professional scientific literature. Their explanation and overview are given in the following table 2.

Table 2. Analyzed criteria

ID	Name of the criterion	Description of criteria
C1	Level of work automation	It measures the tractor's level of autonomy in performing operations (eg automatic steering, autopilot, autonomous operation mode).
C2	Sensor integration (IoT capacity)	Tractor capability for sensor use (soil moisture, temperature, pressure, etc.).
C3	Precision of operations	It measures the accuracy of agricultural operations (sowing, fertilizing, spraying).
C4	Digital connectivity (real-time data)	It evaluates the tractor's ability to exchange data in real time (cloud, farm management systems).
C5	System interoperability	It refers to the compatibility of tractors with different attachments and software (ISOBUS standard).
C6	Analytics and decision support systems	Assessment of the existence and quality of systems that analyze data and provide recommendations (eg when to sow, how much fertilizer to apply).
C7	Resource utilization efficiency	It measures how much the tractor optimizes use.
C8	Predictive maintenance	It refers to the system's ability to predict failures based on data (AI, sensors).
C9	Ease of use	Assessment of how intuitive the system is for the user (farmer/operator).
C10	Digitization costs	Total Cost of Ownership.

Source: Authors

It is important to point out that during the evaluation of the criteria, the fuzzy variant of the multi-criteria method is used. Fuzzy decision making in smart agriculture improves crop yield and quality. In addition, it improves the use of resources, reduces waste and increases efficiency and sustainability. (Erdoğan, 2022)

The procedure we used to evaluate the mentioned criteria is fuzzy simple calculation of weights. The applied method is the SiWeC method of multi-criteria decision-making (Simple weight calculation), and its fuzzy approach was used for the subjective evaluation of the importance of the criteria, relying on the use of linguistic expressions. The method was created by Puška et al. (2024a) and its steps include:

- Assessment of the criteria,
- Construction of fuzzy numbers,
- Normalization fuzzy numbers,

$$\tilde{n}_{ij} = \frac{x_{ij}^l}{\max x_{ij}^u}, \frac{x_{ij}^m}{\max x_{ij}^u}, \frac{x_{ij}^u}{\max x_{ij}^u}$$

Where is $\max x_{ij}^u$ maximum value for all criteria.

- Calculating the standard deviation (*st. dev*_{*j*}),

- Display of normalized results with standard deviation values,

$$\tilde{v}_{ij} = \tilde{n}_{ij} \times st.dev_j$$

- Calculation of total weights for specific criteria,

$$\bar{s}_{ij} = \sum_{j=1}^n \tilde{v}_j$$

- Getting criteria weight.

$$\tilde{w}_{ij} = \frac{s_{ij}^l}{\sum_{j=1}^n s_{ij}^u}, \frac{s_{ij}^m}{\sum_{j=1}^n s_{ij}^m}, \frac{s_{ij}^u}{\sum_{j=1}^n s_{ij}^l}$$

After the obtained results, the validation of the results was carried out, as well as the discussion and making of the necessary conclusions. In addition, certain recommendations were highlighted that should be kept in mind during further similar research in this area.

Results and Discussion

The experts' rating is shown in the following table 1, while the linguistic conversion of the ratings is presented in table 2.

Table 3. Expert assessment

ID	Name of the criterion	e1	e2	e3	e4	e5	e6	e7
C1	Level of work automation	6	7	6	7	6	6	7
C2	Sensor integration (IoT capacity)	4	5	3	7	6	7	7
C3	Precision of operations	7	7	7	7	6	6	7
C4	Digital connectivity (real-time data)	7	6	7	6	6	6	7
C5	System interoperability	5	4	5	5	4	6	5
C6	Analytics and decision support systems	5	4	3	4	3	4	6
C7	Resource utilization efficiency	5	6	5	5	6	6	5
C8	Predictive maintenance	4	5	6	5	6	5	5
C9	Ease of use	6	6	7	6	6	6	7
C10	Digitization costs	5	6	5	7	6	7	6

Source: Authors

Table 4. Linguistic evaluation of criteria

Criteria	e1	e2	e3	e4	e5	e6	e7
C1	G	V-G	G	V-G	G	G	V-G
C2	M	M-G	M-L	V-G	G	V-G	V-G
C3	V-G	V-G	V-G	V-G	G	G	V-G
C4	V-G	G	V-G	G	G	G	V-G
C5	M-G	M	M-G	M-G	M	G	M-G
C6	M-G	M	M-L	M	M-L	M	V-G
C7	M-G	G	M-G	M-G	G	G	M-G

Criteria	e1	e2	e3	e4	e5	e6	e7
C8	M	M-G	G	M-G	G	M-G	M-G
C9	G	G	V-G	G	G	G	V-G
C10	M-G	G	M-G	V-G	G	V-G	G

Source: Authors

By applying all the steps of the used method, the final ratings of the analyzed criteria in tractor digitalization were obtained, and their final ranking is given in the following table 3. From it, we can see that the technical criterion “precision of operations” is the best rated, that is, it has the highest weight (0.118). The criteria “Level of work automation” and “Digital connectivity” follow immediately after, while the criterion “Analytics and decision support systems” has the least weight according to expert evaluation.

Table 5. Rang alternative

Rank	ID	Criteria	\tilde{w}_{ij}
1	C3	Precision of operations	0.118
2	C1	Level of work automation	0.114
2	C4	Digital connectivity (real-time data)	0.114
4	C9	Ease of use	0.112
5	C10	Digitization costs	0.105
6	C7	Resource utilization efficiency	0.097
7	C2	Sensor integration (IoT capacity)	0.096
8	C8	Predictive maintenance	0.090
9	C5	System interoperability	0.083
10	C6	Analytics and decision support systems	0.071

Source: Authors

By comparing with other subjective fuzzy variants of decision-making methods, we get a final overview of the given criteria (table 4). We notice that by applying the other methods we get a very similar final ranking. With the other methods, the criterion “*Precision of operations*” was rated the best, and “*Analytics and decision support systems*” the lowest.

Table 6. Ranking of alternatives using different MCDM methods

Rank	Criteria	ID	FAHP	FBWM	FSWARA
1	Precision of operations	C3	0.135	0.140	0.128
2	Level of work automation	C1	0.128	0.125	0.130
2	Digital connectivity (real-time data)	C4	0.132	0.130	0.125
4	Ease of use	C9	0.125	0.120	0.120
5	Digitization costs	C10	0.122	0.118	0.118
6	Resource utilization efficiency	C7	0.090	0.095	0.092
7	Sensor integration (IoT capacity)	C2	0.085	0.090	0.095
8	Predictive maintenance	C8	0.083	0.085	0.085
9	System interoperability	C5	0.060	0.060	0.065
10	Analytics and decision support systems	C6	0.040	0.037	0.042

Source: Authors

In the last stage, before drawing conclusions in the work, we validated the obtained results in such a way that the ranked results obtained by the FSiWeC method were compared with the ranked results of other methods (fuzzy AHP, fuzzy BWM and fuzzy SWARA) using the Spearman correlation coefficient using the following expression (Božanić et al., 2022):

$$SCC = 1 + \frac{6 \sum_{i=1}^n D_i^2}{n(n^2 - 1)}$$

In this equation, D_i is the difference between the rank of an item in the vector w and the rank of the corresponding item in the reference vector, and n is the number of ranked items. (Božanić et al., 2022). A SCC value of 0 means that there is no relationship between the variables. (Katranci et al., 2025)

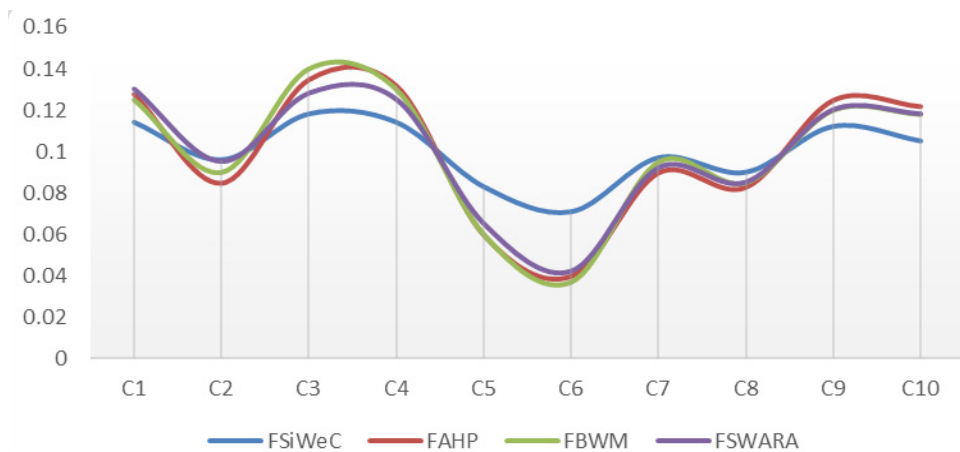
Table 7. Correlation matrix

Methods	FSiWeC	FAHP	FBWM	FSWARA
FSiWeC	1.000	0.945	0.964	0.973
FAHP	0.945	1.000	0.976	0.964
FBWM	0.964	0.976	1.000	0.982
FSWARA	0.973	0.964	0.982	1.000

Source: Authors

The greatest agreement was expressed with the FBWM-FSWARA method ($\rho = 0.982$), which shows that these are almost identical models. The FSiWeC method has the highest compatibility with the FSWARA method ($\rho = 0.973$), while the smallest but still high similarity is with the FAHP method ($\rho = 0.945$). Discrepancies are pronounced due to pairwise comparisons of methods and greater measurement discrimination. Method comparison results shows that the stability of the ranking is high, as well as the reliability of the expert data. The following chart 1 gives us a visualization of that.

Figure 1. Comparison with other subjective MCDM methods



Source: Authors

Precision agriculture research shows that operational accuracy and automation are key factors in improving productivity and lowering costs. At the outset, research in the field of precision agriculture (Wolfert et al., 2017) highlights the importance of digital technologies that enable the improvement of inputs and the improvement of production efficiency, which coincides with the high ranking of criteria C3 and C1 in this research.

Despite methodological rigor and the use of multiple fuzzy MCDM methods, this research has certain limitations that should be considered when interpreting the results. Namely, the research, firstly, relies on a relatively small number of experts ($n=7$), which may affect the representativeness of the results obtained. Although the experts were selected according to relevant skills and experience, a larger sample could increase the robustness and generalizability of the results. Second, subjective assessments of experts were used, which, although shaped through a fuzzy approach, may still have a certain degree of bias. Third, the research was carried out in a specific regional framework (agricultural sector of the Balkans), which may reduce the possibility of applying the results in other countries with a higher degree of digital maturity and more developed infrastructure. Fourth, the model does not include changes over time, ie. the analysis is static and does not take into account the development of technologies and changing market conditions.

In order to improve research and continue the development of the agricultural machinery digitization sector, the following directions of future research are recommended:

- First, subsequent research could include a larger sample of experts, including farmers, policy makers, and technology firms, thus ensuring a broader perspective and greater validity of the findings.
- Second, it is recommended to include objective methods for determining weights (eg Entropy, CRITIC, IDOCRIW), as well as hybrid models that combine subjective and objective methods.
- Third, an important direction of research is the application of advanced fuzzy and hybrid approaches (fuzzy MARCOS, fuzzy MABAC, fuzzy TOPSIS), along with integration with group decision-making methods (group decision-making).
- Fourth, further research can include dynamic models and time series, with the aim of studying the evolution of the importance of criteria over time, especially in the context of the rapid advancement of digital technologies.
- Fifth, it is recommended to combine the digital twin system with AI models, in order to enable simulations of various scenarios and optimization of decisions in real time.

Conclusions

In the paper, evaluation and ranking of tractor digitization criteria was carried out using the fuzzy multi-criteria decision-making method. Based on the collected evaluations of experts and the application of the fuzzy SiWeC method, the key criteria with the most significant impact on the digitalization process were determined. Research has

shown that the criteria of Precision of operations (C3), the level of automation of work processes (C1) and digital connectivity (C4) are of key importance, while the criteria of system interoperability (C5) and analytics, and decision support systems (C6) have less impact.

As part of the validation of the results, a comparative analysis was performed using fuzzy AHP, fuzzy BWM and fuzzy SWARA methods. The obtained results show a high degree of agreement between the methods, which is confirmed by the high values of the Spearman correlation coefficients. This type of consistency confirms the robustness of the model and the reliability of the criterion ranks that were obtained.

Research shows that the digitalization of agricultural machinery is currently focused on improving operational efficiency and optimizing resources, while advanced features such as analytical systems and full interoperability are still less of a priority. This has significant consequences for decision makers, technology producers and agricultural policy makers.

Acknowledgements

Paper is a part of research financed by the MSTDI RS, agreed in decision no. 451-03-33/2026-03/200009 from 5.2.2026.

Conflict of interests

The authors declare no conflict of interest.

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