Journal of Agricultural Sciences (Tarim Bilimleri Dergisi) 2025, 31 (3) : 732 – 746 DOI: 10.15832/ankutbd.1571732

Journal of Agricultural Sciences
(Tarim Bilimleri Dergisi)

J Agr Sci-Tarim Bili
e-ISSN: 2148-9297
jas.ankara.edu.tr

JAS

Evaluation of Smart Agricultural Technologies Used in Smart Villages: SWARA Approach

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ARTICLE INFO
Research Article
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Received: 22 October 2024 / Revised: 09 January 2025 / Accepted: 06 February 2025 / Online: 29 July 2025

Cite this article
Öztaş Karlı R G (2025). Evaluation of Smart Agricultural Technologies Used in Smart Villages: SWARA Approach. *Journal of Agricultural Sciences (Tarim Bilimleri Dergisi),* 31(3):732-746. DOI: 10.15832/ankutbd.1571732

ABSTRACT
The rapid development of technology has paved the way for innovative solutions in agriculture, particularly in smart villages. This study evaluates the effectiveness and sustainability of agricultural technologies used in smart villages by employing the SWARA (Stepwise Weight Assessment Ratio Analysis) method. Six main criteria and eighteen sub-criteria were assessed based on expert evaluations.

The findings reveal that technological relevance (0.267) is the most significant criterion, followed by efficiency and performance (0.205), economic factors (0.164), environmental sustainability (0.137), social and user satisfaction (0.119), and political and governance factors (0.108). Among the sub-criteria, innovativeness, yield increase, and cost-effectiveness were identified as critical factors influencing the adoption of smart agricultural technologies.

The study offers actionable recommendations, including prioritizing user-friendly and cost-effective technologies, enhancing financial incentives, and aligning policies with global sustainability goals such as SDG 2 (Zero Hunger) and SDG 12 (Responsible Consumption and Production). Furthermore, it emphasizes the importance of stakeholder collaboration, locally specific strategies, and continuous adaptation of technologies to regional needs, ensuring the sustainable development of smart villages.

Keywords: Agricultural technologies, smart agriculture, smart village, SWARA

1. Introduction

In recent years, digital transformation and the use of smart technologies in agricultural production have led to significant changes in the agricultural sector (Kılavuz & Erdem 2019). The concept of smart villages has emerged to increase the efficiency of agricultural production, optimize resource use and promote sustainable agricultural practices (Öztaş Karlı et al. 2023). Smart villages address the development of rural areas from a broader socio-economic perspective, as they include components such as community participation, local identity and local economy in addition to various technologies and sustainable practices (Öztaş, 2019). This concept also directly contributes to the United Nations' Sustainable Development Goals (SDGs) of "Zero Hunger" (SDG 2), "Decent Work and Economic Growth" (SDG 8) and "Responsible Consumption and Production" (SDG 12) (United Nations 2024).

In contrast, smart agriculture is a technique that optimizes soil and crop management in order to increase agricultural productivity, make more economical use of resources and minimize environmental impacts (Kour & Arora 2020). In this context, effectively evaluating agricultural technologies and identifying the most appropriate technologies are critical for the success of smart villages. However, there are limited studies in the existing literature that provide a comprehensive assessment of agricultural technologies in this context.

Research on smart villages has primarily focused on their technological aspects (Somwanshi et al. 2016; Anderson et al. 2017). Subsequently, studies have explored how these initiatives can effectively benefit rural communities (Philip & Williams 2019; Acosta et al. 2021). As Zavratnik et al. (2018) note, much of the research in this area remains case-based rather than theoretically grounded. When the studies on smart agriculture that use Criteria Combination Methodology (CCM) are examined, Uztürk and Büyüközkan (2022) used 2-Tuple Linguistic (2-TL) DEMATEL technique, 2-TL-MARCOS in technology evaluation for smart agriculture. Rajkumar et al. (2023) used Weighted Sum Model (WSM) in crop selection. Muhsen and Al-hchaimi (2024) integrated Opinion Weighted Criteria Method (OWCM) and TODIM to rank smart agriculture decision support tools. Büyük et al. (2021) evaluated all the criteria created for the digital maturity assessment model for the agricultural sector using the Best-Worst Method (BWM). Morkunas & Volkov (2023) created climate-smart agriculture indicators and used SAW, TOPSIS, and VIKOR MCDM methods in their study. Abualkishik et al. (2022) evaluated smart agricultural production efficiency with the Fuzzy MARCOS Method.

Considering criteria such as efficiency, sustainability and user satisfaction in agricultural production, determining the most appropriate agricultural technologies to be used in smart villages is an important problem. Existing evaluation methods lack a comprehensive analysis of these technologies according to various criteria. This leads to difficulties for decision makers in selecting the most appropriate technologies and inefficient use of resources.

SWARA method is a method used effectively in MCDM processes (Keršuliene et al. 2010). The Stepwise Weight Assessment Ratio Analysis (SWARA) method provides a step-by-step approach in determining the importance of criteria and enables a more precise calculation of criteria weights (Zolfani & Banihashemi 2014). This method makes it possible to evaluate agricultural technologies in a multidimensional and detailed manner.

There is a significant research gap in the existing research on systematic comparison of agricultural technologies according to various criteria and identification of optimal technologies. In order to fill this gap, this study presents a multi-criteria evaluation of agricultural technologies using the SWARA method, which was created by Keršuliene, Zavadskas, and Turskis in 2010 (Keršuliene et al. 2010). In this context, the study's hypothesis is: “The SWARA method is a more effective approach than other MCDM methods for evaluating agricultural technologies comprehensively and reliably”.

The aim of the present study is to evaluate the effectiveness and sustainability of agricultural technologies used in smart villages. The study differs from other studies in the literature in that it comprehensively evaluates smart agricultural technologies using 6 main and 18 sub-criteria and uses SWARA, a different MCDM method.

The contributions of this study can be summarized as follows: SWARA method will provide a comprehensive assessment of agricultural technologies used in smart villages. Making the multi-criteria decision-making process more systematic and reliable will help decision makers make more informed and effective choices. Identifying the most appropriate technologies that will increase efficiency, sustainability and user satisfaction in agricultural production will contribute significantly to the success of smart villages. According to the results obtained, recommendations will be presented for the development of policies and strategies that encourage the use of agricultural technology.

This study differs from existing research by applying the SWARA method, for determining criteria weights and evaluating technologies comprehensively. Unlike previous studies (Uztürk & Büyüközkan 2022; Rajkumar et al. 2023; Muhsen & Al-hchaimi 2024) that often rely on single or less adaptable methods, this study integrates expert judgments in a stepwise manner, addressing multidimensional criteria and filling a critical methodological gap in the field.

2. Smart Village Concept

The smart village concept is an approach that has gained increasing importance in the field of agriculture and rural development in recent years (Öztaş 2019; Zhang & Zhang 2020; Stoian et al. 2022). This concept aims at the social, economic and environmental development of rural areas through the integration of digital technologies, innovative solutions and sustainable practices (Öztaş Karlı 2020). Smart villages aim to increase the efficiency of agricultural production, improve the quality of rural life and ensure environmental sustainability by supporting the transition from traditional agricultural methods to smart agricultural practices (Öztaş Karlı et al. 2023).

There are many definitions of smart villages. International organizations supporting smart village initiatives (ENRD, CGIAR and IEEE) emphasize the diversity of technological and socio-economic aspects that smart villages can cover. For example, Consultative Group on International Agricultural Research (CGIAR) focuses on climate-smart technologies and agriculture (CGIAR 2022), while Institute of Electrical and Electronics Engineers (IEEE) defines smart villages as a combination of renewable energy, community-based education and entrepreneurial opportunities (SVI 2019). The role of communities and opportunities is central to European Network for Rural Development’s (ENRD) definition, which, perhaps surprisingly, does not refer to a specific technology (ENRD 2018). In contrast, academic definitions explicitly link smart villages to the application of information and communication technology (ICT) and data technologies in a rural setting.

Smart villages optimize agricultural production using a variety of smart technologies and innovative solutions. These technologies include sensors, drones, artificial intelligence, big data analytics, internet of things (IoT) and digital platforms (Bin Muhammad et al. 2022; Adli et al. 2023). The integration of these technologies enables more efficient management of agricultural processes and provides farmers with more accurate and timely information (Kour & Arora 2020). For example, soil moisture sensors optimize irrigation needs by monitoring plant growth, while drones can be used for tasks such as field monitoring and pest control, saving labor and time (Mekala & Viswanathan 2017).

Another important component of smart villages is social and economic development. Digital technologies and innovative solutions create new job opportunities in rural areas, increase the interest of young people in agriculture, and enhance the attractiveness of rural life. Moreover, smart villages encourage more active participation of local communities in decision-making processes and enable more effective implementation of rural development policies (Zavratnik et al. 2018; Öztaş 2019).

The smart village concept also aims at environmental sustainability. Environmental goals such as the efficient use of natural resources, waste management, energy efficiency and reducing carbon footprint are key components of smart villages (Gerli et al. 2022). In this context, the efficient use of water and energy resources used in agricultural production, the integration of renewable energy sources and the dissemination of environmentally friendly agricultural practices are of great importance.

As a result, smart villages stand out as a concept that supports the sustainable development of rural areas through digital transformation and innovative solutions. In line with the goals of increasing productivity in agricultural production, improving the quality of rural life and environmental sustainability, smart villages will play an important role in future agricultural and rural development policies. In this context, effective and comprehensive utilization of agricultural technologies is critical for the success of smart villages.

2.1.1. Smart agriculture technologies

Smart agricultural technologies are an approach that aims to use digital tools and innovative solutions to optimize agricultural production processes and increase productivity (Kour & Arora 2020). These technologies enable farmers to manage agricultural activities more effectively by providing farmers with greater control, accuracy and data-based decision-making (Jiang et al. 2015). Smart agriculture involves the integration of various technologies such as sensors, drones, artificial intelligence (AI), big data analytics, and the internet of things (IoT) (Jiang et al. 2015; Mekala & Viswanathan 2017; Carrer et al. 2022).

2.1.2. Sensors and IoT

Sensors are used to monitor various parameters in agricultural fields. Soil moisture sensors measure the moisture level in the soil to optimize irrigation systems and save water. Weather sensors monitor plant growth conditions by collecting meteorological data such as temperature, humidity, precipitation and wind speed. These sensors, coupled with IoT devices, provide real-time data to farmers and enable automated management of agricultural processes (Jiang et al. 2015; Muangprathub et al. 2019; Kour & Arora 2020).

2.2.3. Drones and satellite imaging

Drones and satellite imaging technologies play an important role in monitoring farmland. Drones take high-resolution images and monitor issues such as plant health, the spread of pests and irrigation needs. These images provide farmers with a detailed picture of the condition of their fields and enable them to make necessary interventions in a timely manner (Al-Shareeda et al. 2022). Satellite imagery, on the other hand, allows continuous monitoring of large agricultural areas and large-scale agricultural strategies are developed by analyzing large data sets (Htitiou et al. 2020).

2.2.4. Artificial intelligence and big data analytics

Artificial intelligence (AI) and big data analytics are important tools for processing and analyzing agricultural data. Artificial intelligence analyzes collected data to make predictions on topics such as crop growth models, pest predictions and productivity analysis. Big data analytics provides farmers with information on best practice strategies by analyzing the relationships between historical data and current conditions. In this way, agricultural production processes become more efficient and sustainable (Jiang et al. 2015).

2.2.5. Smart irrigation systems

Smart irrigation systems are designed to ensure efficient use of water resources. Using information from soil moisture sensors and weather data, these systems optimize the timing and quantity of irrigation. Automated irrigation systems meet the needs of plants by using only as much water as needed and avoid wasting water. This contributes to the sustainable management of water resources (Malche et al. 2017; Soni et al. 2018; Al-Ali et al. 2019).

2.2.6. Robotics and automation

Agricultural robots are used in various agricultural tasks such as sowing, harvesting, weed control and plant care. These robots reduce agricultural labor and make agricultural processes faster and more efficient. For example, harvesting robots accurately pick fruits and vegetables, minimizing human error and improving product quality. Automation systems enable agricultural equipment and machinery to operate automatically, saving labor and time (Cubero et al. 2020; Gorlov et al. 2020; Singh & Kaur 2021).

2.2.7. Digital agriculture platforms

Digital agriculture platforms allow farmers to manage, analyze and share their agricultural data. These platforms provide various services such as agricultural consultancy, market information, weather forecasts, and agricultural input management (Jiang et al. 2015). Through these platforms, farmers can plan and manage their agricultural activities more effectively. Moreover, digital platforms increase information sharing and collaboration among farmers, leading to rapid adoption of agricultural innovations.
In conclusion, smart agriculture technologies offer a wide range of digital tools and innovative solutions to make agricultural production processes more efficient, sustainable and profitable. The integration of these technologies enables more precise and data-driven management of agricultural activities, significantly increasing agricultural productivity and sustainability. The effective use of these technologies in smart villages has great potential for the future of rural development and agricultural production. However, ensuring the effective use and sustainability of smart agricultural technologies requires a comprehensive evaluation based on various criteria.

3. Material and Methods

In this study, SWARA method was used to evaluate agricultural technologies used in smart villages. The data used in the study were obtained through literature review and expert evaluation. The literature review provided comprehensive information about the agricultural technologies used in smart villages and the criteria used in the evaluation of these technologies. Scopus database was used to search academic articles. Scopus was chosen because it has a larger database that covers almost all journals indexed by web of science (WoS). The key search terms for the literature review were "smart village" OR "smart rural" OR "smart agriculture" OR "agriculture technology" OR "agricultural technologies" OR "digital agriculture" OR "agriculture 4.0" OR "smart farming". The main criteria and sub-criteria were prioritized by expert evaluation. The expert group is presented in Table 2. Pairwise comparison matrices created for SWARA analysis were prepared in Excel format and data were collected by sending them to the experts via e-mail.

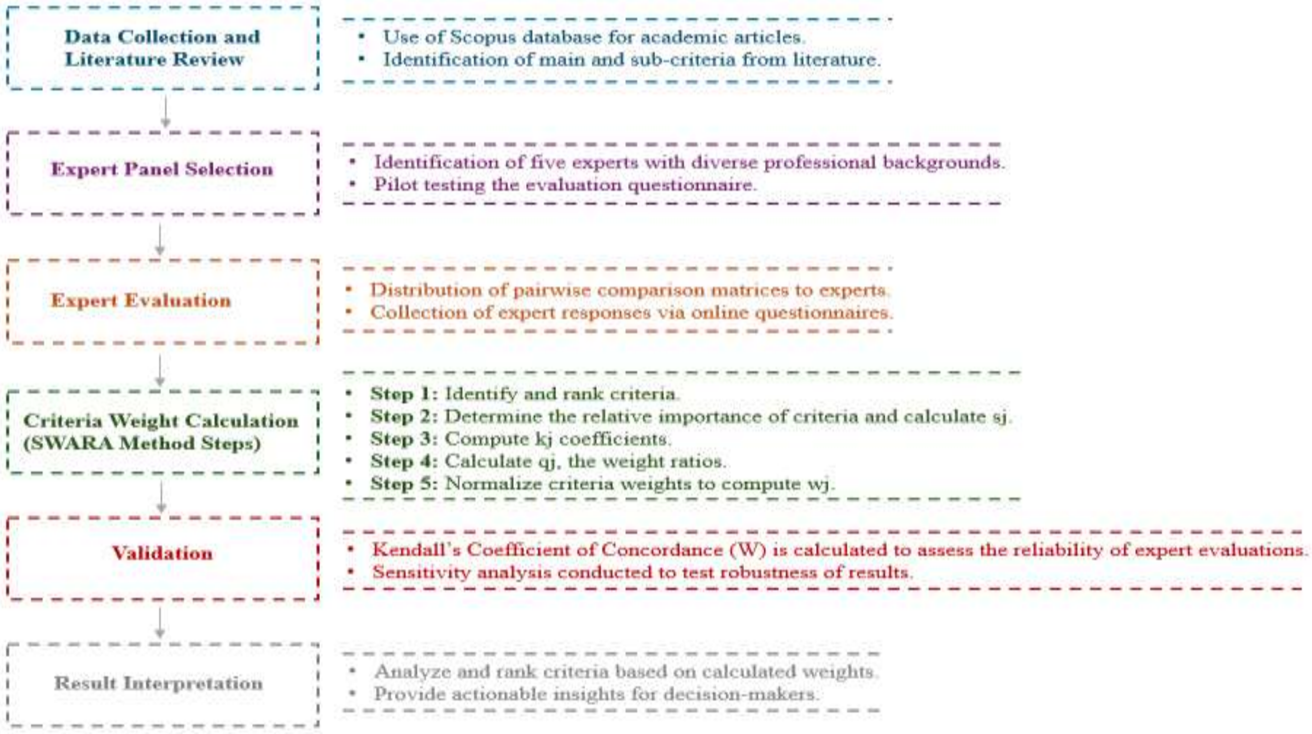

Figure 1- Methodological flowchart

3.1. SWARA method

SWARA method, one of the MCDM, was introduced in 2010. In SWARA method, the expert has a critical role in evaluations and calculation of weights (Zolfani & Saparauskas 2013). This method enables experts to estimate the importance of the criteria in the process of determining the weights. It is effective in collecting and coordinating the data obtained from experts. Experts also have important roles in the evaluation of the calculated weights. Each expert determines the importance of each criterion based on their knowledge, experience and experience (Shahsavar et al. 2019). The biggest advantage of the method is the ease of application of mathematical operations, as well as taking expert opinions in criteria weight calculation (Keršuliene et al. 2010; Zolfani & Saparauskas 2013; Zolfani & Banihashemi 2014).

The process of determining the relative weights of the criteria using the SWARA method is carried out using the following steps (Utlu 2024).

Step 1: Identifying criteria and experts

It is assumed that there are n criteria (K_j, j=1,2,3. n) and k experts (KV_k, k=1,2,3. n). As a result of the literature review, the relevant criteria were identified and a total of 6 main criteria and 18 sub-criteria were listed. The criteria and sub-criteria selected to address the existing research gaps and particularly the practical needs in the field of agricultural and rural development are shown in Table 1.

Table 1- Criteria and sub-criteria used in the evaluation of agricultural technologies

Criteria	*Sub-criteria*	*Description*	*Reference*
Technological relevance	Innovativeness	How innovative the technology is and how it fits with existing agricultural practices.	Büyüközkan & Uztürk 2024; Castiblanco Jimenez et al. 2021; Cornejo-Velazquez et al. 2022; Cesco et al. 2023; Del Río Castro et al. 2021; Gabriel & Gandorfer 2023; Mishbah et al. 2018
	Ease of use	How easily technology can be used by farmers.	
	Compatibility	Compatibility with existing agricultural equipment and systems.	
Efficiency and performance	Yield increase	How much technology has increased productivity in agricultural production.	Balafoutis et al. 2020; Cesco et al. 2023; Del Río Castro et al. 2021; Elijah et al. 2018; Karunathilake et al. 2023; Marcu et al. 2020; Raji et al. 2024; Rehman et al. 2023
	Time saving	Savings in terms of labor and time.	
	Precision	Accuracy of data and applications enabled by technology.	
Economic factors	Regulatory compliance	Whether the initial and operating costs of the technology are reasonable.	Amadu et al. 2020; Balafoutis et al. 2020; Darnhofer et al. 2010; Mutenje et al. 2019; Raji et al. 2024; Yigezu et al. 2018
	Supportive policies	Return on investment against the benefits of technology.	
	Administrative facilities	Government incentives and financial support opportunities.	
Environmental sustainability	Energy efficiency	The level of energy consumption of the technology.	Adewale et al. 2019; Balafoutis et al. 2020; Büyüközkan & Uztürk 2024; Cesco et al. 2023; Engler & Krarti 2021; Gobarah et al. 2015; Raji et al. 2024; Rehman et al. 2023; Watson 2019
	Carbon footprint	Impact of irrigation technologies on water conservation.	
	Water saving	Environmental impact of technology and carbon emissions.	
Social and user satisfaction	Acceptance	The degree of technology adoption by farmers and the community.	Baran & Ersoy Karaçuha 2021; Büyüközkan & Uztürk 2024; Castiblanco Jimenez et al. 2021; Del Río Castro et al. 2021; Sennuga & Oyewole 2020
	Health and safety	Level of training and information required for the use of technology.	
	Education and information	The impact of the use of technology on occupational health and safety.	
Political and governance factors	Regulatory compliance	Alignment of technology with existing agricultural policies and regulations.	Castiblanco Jimenez et al. 2021; Kuhlmann 2015; Ntaliani et al. 2010; Tey & Brindal 2012; Zhang & Zhang 2020
	Supportive policies	Existence of policies that encourage the use of technology.	
	Administrative facilities	The managerial infrastructure needed to manage and oversee the technology.	

In the process of evaluating the criteria, online questionnaires were used. The questionnaires were evaluated by 5 experts between 20.08.2024-30.09.2024. These experts were selected based on their professional expertise and relevance to the criteria being assessed, ensuring a comprehensive understanding of agricultural technologies. Their qualifications and professional backgrounds are detailed in Table 2.

To ensure a balanced and informed evaluation of the criteria, thereby enhancing the reliability of the study, the panel members were selected with great care. First, a professor of agricultural sciences and an urban planner working in the public sector were included to address agricultural technologies from both academic and policy perspectives. Additionally, an associate professor specializing in smart agriculture was involved to evaluate the integration of technological solutions into agricultural practices. An agricultural engineer was added to provide technical contributions in assessing the practicality and effectiveness of agricultural technologies. The final panel member is an expert focused on the latest developments in smart agricultural technologies.

In addition, a pilot test was conducted with five independent experts to ensure the reliability and validity of the online survey, and the final version of the survey was developed by making minor adjustments.

Table 2- Expert group details

Expert	*Title*	*Experience*	*Sector/Working Area*
1	Professor	19 years	Agriculture Sciences
2	Urban Planner	11 years	Public Sector
3	Associate Professor	13 years	Smart Agriculture
4	Agricultural Engineer (m.sc)	14 years	Agricultural Technologies
5	Smart Agriculture Technologies Expert	12 years	Smart Agriculture

To ensure the reliability of expert evaluations, Kendall's Coefficient of Concordance (W) was calculated. This method measures the level of agreement among multiple experts. Each expert's weight assignments were converted into rankings, and the ranks were analyzed using the Equation 1.

$$W = \frac{12.S}{k^2.(n^3 - n)} \tag{1}$$

Where; $k = 5$ (number of experts) and $n = 6$ (number of criteria). A W value closer to 1 indicates stronger agreement. For this study, the calculated W value was 0.85, demonstrating a high level of consensus among the experts.

Step 2: Determining the order of importance of criteria

The level of importance of each criterion is determined by experts. Experts rank the criteria from most important to least important.

Step 3: Determining the coefficient s_j

Once the order of importance of the criteria has been determined, each criterion is compared with the next. For example, how (%) important is the top criterion compared to the second criterion, and how (%) important is the second criterion compared to the third criterion. By posing these questions to the experts, the average importance of each comparison is determined and this value is expressed as "s_j". Experts make this assessment in five-point increments between 0 and 1, so the values can be set to 0.00, 0.05, 0.10, 0.15, 0.20, 0.25, 0.30, 0.35, 0.40, 0.45, 0.50, 0.55, 0.60, 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95 and 1.00 respectively. This five-point increment choice was used to avoid complicating the evaluation process and to ensure that experts could make consistent assessments. Here, a value of 0 indicates that the two criteria are equally important, while a value of 0.20 indicates that the first ranked criterion is 20% more important than the criterion immediately following it.

Step 4: Determining the k_j coefficient

The coefficient (k_j) is calculated for each criterion. 1 point is added to the sj value (Equation 2).

$$k_j = \begin{cases} 1 & j = 1 \\ s_j + 1 & J > 1 \end{cases} \tag{2}$$

Step 5: Determination of q_j coefficient

The importance vector q_j is calculated according to Equation 3 for all criteria. qj, is the weight ratio of each criterion compared to the previous criterion. q_j is calculated based on the value of s_j. The adjusted weight value of the most important criterion is 1.

$$q_j = \begin{cases} 1 & j = 1 \\ \frac{q_{j-1}}{k_j} & J > 1 \end{cases} \tag{3}$$

Step 6: Determination of the relative weights (w_j) of the criteria

As stated in Equation 4, the final weight of each criterion (w_j) is determined by dividing the criteria weights (q_j) by the sum of the weights of the criteria.

$$w_j = \frac{q_j}{\sum_{k=1}^{n} q_k} \tag{4}$$

The main criteria and sub-criteria were evaluated in order of importance by five different experts and the relative weights of these criteria were calculated by SWARA method. This normalization formula (Equation 3) is widely used in MCDM methods as it ensures that the total of relative weights (w_j) of all criteria equals 1. Furthermore, this formula is preferred in this study over other normalization techniques due to its simplicity and efficiency.

4. Results

4.1. Evaluation of main criteria

Tables 3-7 present the SWARA analysis results for each expert, showing the relative weights of each criterion/sub-criteria and the analysis process. These tables provide a detailed illustration of how each expert's evaluation contributed to the overall assessment process.

Table 3- SWARA analysis results for expert 1

Rank	*Criteria*	s_j	k_j	q_j	w_j
1	Technological relevance	-	1.000	1.000	0.264
2	Efficiency and performance	0.30	1.30	0.769	0.203
3	Economic factors	0.25	1.25	0.615	0.163
4	Environmental sustainability	0.20	1.20	0.513	0.135
5	Social and user satisfaction	0.10	1.10	0.466	0.123
6	Political and governance factors	0.10	1.10	0.424	0.112
	Total	-	-	-	1.000

Table 4- SWARA analysis results for expert 2

Rank	*Criteria*	s_j	k_j	q_j	w_j
1	Technological relevance	-	1.000	1.000	0.225
2	Efficiency and performance	0.20	1.20	0.833	0.188
3	Economic factors	0.15	1.15	0.725	0.163
4	Environmental sustainability	0.10	1.10	0.659	0.148
5	Social and user satisfaction	0. 05	1.05	0.627	0.141
6	Political and governance factors	0.05	1.05	0.597	0.135
	Total	-	-	-	1.000

Table 5- SWARA analysis results for expert 3

Rank	*Criteria*	s_j	k_j	q_j	w_j
1	Technological relevance	-	1.000	1.000	0.291
2	Efficiency and performance	0.40	1.40	0.714	0.208
3	Economic factors	0.30	1.30	0.549	0.160
4	Environmental sustainability	0.25	1.25	0.440	0.128
5	Social and user satisfaction	0. 15	1.15	0.382	0.111
6	Political and governance factors	0.10	1.10	0.347	0.102
	Total	-	-	-	1.000

Table 6- SWARA analysis results for expert 4

Rank	*Criteria*	s_j	k_j	q_j	w_j
1	Technological relevance	-	1.000	1.000	0.280
2	Efficiency and performance	0.35	1.35	0.740	0.207
3	Economic factors	0.30	1.30	0.570	0.159
4	Environmental sustainability	0.25	1.25	0.475	0.133
5	Social and user satisfaction	0. 15	1.15	0.413	0.116
6	Political and governance factors	0.10	1.10	0.413	0.105
	Total	-	-	-	1.000

Table 7- SWARA analysis results for expert 5

Rank	*Criteria*	s_j	k_j	q_j	w_j
1	Technological relevance	-	1.000	1.000	0.245
2	Efficiency and performance	0.25	1.25	0.800	0.197
3	Economic factors	0.20	1.20	0.666	0.164
4	Environmental sustainability	0.15	1.15	0.580	0.142
5	Social and user satisfaction	0. 10	1.10	0.527	0.129
6	Political and governance factors	0.05	1.05	0.502	0.123
	Total	-	-	-	1.000

The determined importance degrees (s_j), calculated weight ratios (q_j), criterion weights (w_j) and normalized weights (N_j) of the criteria scored by each expert shown in Tables 3-7 are combined and shown in Table 8.

Table 8- Mean values

Criteria	s_j	q_j	w_j
Technological relevance	-	1.000	0.267
Efficiency and performance	0.30	0.769	0.205
Economic factors	0.25	0.615	0.164
Environmental sustainability	0.20	0.513	0.137
Social and user satisfaction	0.15	0.446	0.119
Political and governance factors	0.10	0.405	0.108
Total	-	-	1.000

According to Table 8, technological relevance is considered the most important main criterion with the highest criterion weight (0.267). Efficiency and performance were identified as the second most important main criterion (0.205). The other main criteria are economic factors (0.164), environmental sustainability (0.137), social and user satisfaction (0.119) and political and governance factors (0.108).

4.2. Evaluation of sub-criteria

Table 9 shows the relative importance and weights of the sub-criteria of innovativeness, ease of use and compatibility under the main criterion of technological relevance.

Table 9- SWARA analysis results of the sub-criteria under the main criteria of technological relevance

Criteria	*Sub-Criteria*	s_j	k_j	q_j	w_j
Technological relevance	Innovativeness	-	1.000	1.000	0.419
	Ease of use	0.30	1.30	0.769	0.323
	Compatibility	0.25	1.25	0.615	0.258

According to Table 9, innovativeness is the most important sub-criteria with the highest criterion weight (0.419). Ease of use is the second most important sub-criterion (0.323) and compatibility is the third most important sub-criterion (0.258). Table 10 shows the relative importance and weights of the sub-criteria under the efficiency and performance criterion: Efficiency gains, time savings and precision.

Table 10- SWARA analysis results of the sub-criteria under the main criteria of efficiency and performance

Criteria	*Sub-Criteria*	s_j	k_j	q_j	w_j
Efficiency and performance	Yield increase	-	1.000	1.000	0.433
	Time saving	0.35	1.35	0.741	0.320
	Precision	0.30	1.30	0.570	0.247

According to Table 10, Yield increase is considered the most important sub-criteria with the highest criterion weight (0.433). Time saving is the second most important sub-criterion (0.320) and Precision is the third most important sub-criterion (0.247). Table 11 shows the relative importance and weights of cost effectiveness, return on investment and financial support sub-criteria under the economic factors criterion.

Table 11- SWARA analysis results of the sub-criteria under the main criteria of economic factors

Criteria	*Sub-Criteria*	s_j	k_j	q_j	w_j
Economic factors	Cost effectiveness	-	1.000	1.000	0.427
	Return on investment	0.30	1.30	0.769	0.329
	Financial support	0.35	1.35	0.570	0.244

According to Table 11, cost effectiveness is considered the most important sub-criterion with the highest criterion weight (0.427). Return on investment is the second most important sub-criterion (0.329) and financial support is the third most important (0.244). Table 12 shows the relative importance and weights of energy efficiency, carbon footprint and water saving sub-criteria under the environmental sustainability criterion.

Table 12- SWARA analysis results of the sub-criteria under the main criteria of environmental sustainability

Criteria	*Sub-Criteria*	s_j	k_j	q_j	w_j
Environmental sustainability	Energy efficiency	-	1.000	1.000	0.433
	Carbon footprint	0.35	1.35	0.741	0.320
	Water saving	0.30	1.30	0.570	0.247

According to Table 12, energy efficiency is considered the most important sub-criterion with the highest criterion weight (0.433). Carbon footprint is the second most important sub-criterion (0.320) and water saving is the third most important (0.247). Table 13 shows the relative importance and weights of the sub-criteria of acceptance, health and safety and education and information under the social and user satisfaction criterion.

Table 13- SWARA analysis results of the sub-criteria under the main criteria of social and user satisfaction

Criteria	*Sub-Criteria*	s_j	k_j	q_j	w_j
Social and user satisfaction	Acceptance	-	1.000	1.000	0.406
	Health and safety	0.25	1.25	0.800	0.324
	Education and information	0.20	1.20	0.667	0.270

According to Table 13, acceptance was rated as the most important sub-criterion with the highest criterion weight (0.406). Health and safety are the second most important sub-criterion (0.324), while education and information is the third most important (0.270). Table 14 shows the relative importance and weights of the sub-criteria of regulatory compliance, supportive policies and administrative facilities under the political and administrative factors criterion.

Table 14- SWARA analysis results of the sub-criteria under the main criteria of political and administrative factors

Criteria	*Sub-Criteria*	s_j	k_j	q_j	w_j
Political and administrative factors	Regulatory compliance	-	1.000	1.000	0.419
	Supportive policies	0.30	1.30	0.769	0.323
	Administrative facilities	0.35	1.25	0.615	0.258

According to Table 14, regulatory compliance is rated as the most important sub-criterion with the highest criterion weight (0.419). Supportive policies are the second most important sub-criterion (0.323) and administrative facilities is the third most important sub-criterion (0.258). Table 15 shows the combined mean values for the sub-criteria.

Table 15- Combined mean values for sub-criteria

Criteria	*Sub-Criteria*	s_j	k_j	w_j
Technological relevance	Innovativeness	-	1.000	0.419
	Ease of use	0.30	1.30	0.323
	Compatibility	0.35	1.25	0.258
Efficiency and performance	Yield increase	-	1.000	0.433
	Time saving	0.35	1.35	0.320
	Precision	0.30	1.30	0.247
Economic factors	Cost effectiveness	-	1.000	0.427
	Return on investment	0.30	1.30	0.329
	Financial support	0.35	1.35	0.244
Environmental sustainability	Energy efficiency	-	1.000	0.433
	Carbon footprint	0.35	1.35	0.320
	Water saving	0.30	1.30	0.247
Social and user satisfaction	Acceptance	-	1.000	0.406
	Health and safety	0.25	1.25	0.324
	Education and information	0.20	1.20	0.270
Political and administrative factors	Regulatory compliance	-	1.000	0.419
	Supportive policies	0.30	1.30	0.323
	Administrative facilities	0.25	1.25	0.258

Finally, to ensure the robustness of the findings, a sensitivity analysis was conducted to evaluate how changes in the criteria weights influenced the rankings. The normalized weight (N_j) of each criterion was adjusted by ±10% and ±20%, while maintaining the overall weight normalized to 1. The relative rankings of the criteria were recalculated for each variation, and the results are presented in Table 16.

The analysis revealed that the rankings of the criteria remained consistent across the tested weight variations. For instance, 'Technological Relevance' consistently ranked as the most important criterion, even under the most extreme variation of ±20%, while ‘Efficiency and Performance’ consistently held the second position in all scenarios. These results indicate that the importance of these criteria is robust and resilient to moderate changes in their assigned weights.

Table 16- Sensitivity analysis results

Criteria	*-20%*	*-10%*	*Original (N_j)*	*+10%*	*+20%*
Technological relevance	0.214	0.240	0.267	0.294	0.320
Efficiency and performance	0.164	0.185	0.205	0.226	0.146
Economic factors	0.131	0.148	0.164	0.180	0.197
Environmental sustainability	0.110	0.123	0.137	0.151	0.164
Social and user satisfaction	0.095	0.107	0.119	0.130	0.143
Political and governance factors	0.086	0.097	0.108	0.119	0.130

Although minor fluctuations were observed among the lower-ranked criteria (e.g., “Political and Governance Factors” and “Social and User Satisfaction”), these changes did not significantly affect the relative importance of the criteria or the overall findings. This stability underscores the credibility of the evaluation process and confirms that the assigned weights accurately reflect the inherent importance of each criterion.

5. Discussion

In this study, SWARA method was used to evaluate the effectiveness and sustainability of agricultural technologies used in smart villages. The main criteria and sub-criteria identified in the study were analyzed based on expert assessments. The results are critical for strategic planning, resource allocation and policy development processes.

When the main criteria are evaluated, technological relevance, with the highest criterion weight (0.267), emerges as the most important main criterion. Technological relevance refers to how innovative and useful agricultural technologies are in the context of smart villages. The importance of this criterion is directly related to the advantages that innovations and technological developments in agricultural production provide to farmers. In particular, the integration of technologies into existing agricultural infrastructure and their user-friendly features enhance the speed and efficiency with which farmers adopt these technologies (Gabriel & Gandorfer, 2023). In this context, when selecting technologies for use in smart villages, their compatibility with existing agricultural infrastructure and ease of use should be prioritized. Additionally, factors such as region, culture, and digital literacy influence people's acceptance and adoption of technology (Ashraf et al. 2014; Jin et al. 2024). Therefore, policies developed in this area should be locally specific. For example, in regions with high levels of digital literacy or advanced agricultural systems, innovations can be easily adopted and integrated (Deichmann et al. 2016; Yang et al. 2024). However, in regions with limited access to technology or low levels of digital literacy, resistance may be encountered. Farmers may be reluctant to adopt agricultural technologies due to insufficient knowledge and awareness (Acemoglu 2002; Yang et al. 2024). Communities with traditional agricultural practices, in particular, may exhibit social resistance, further complicating the adoption of these technologies. To overcome these barriers, it is crucial to promote the adoption of agricultural technologies and enhance user satisfaction (Yang et al. 2024). Simpler and more cost-effective solutions can be introduced, particularly in underdeveloped regions. Additionally, technological training programs can be organized to help farmers adopt new technologies more quickly. Furthermore, incentives for the development of local and national technologies should be increased to encourage widespread use and integration.

Efficiency and performance (0.205) is the second most important main criterion. The high weight value of this criterion reveals that agricultural technologies are critical for increasing productivity and improving performance. Productivity and performance means increased agricultural production and more efficient use of resources. This enables farmers to achieve higher crop yields using fewer inputs and ensure the sustainability of agricultural activities (Raji et al. 2024). Proper integration of technologies will make farmers' daily operations more efficient and save labor (Balafoutis et al. 2020). At this point, technologies should be integrated into the daily workflow of farmers and support services should be provided for the maintenance and repair of technological devices. Performance measurement criteria should be developed to regularly assess the long-term impact of technologies.

The third criterion is economic factors (0.164). Economic factors are a crucial criterion in terms of cost-effectiveness and return on investment. This criterion ensures that agricultural technologies are economically sustainable for farmers and provide a reliable return on investments. Economic sustainability enhances continuity and competitiveness in agricultural production (Darnhofer et al. 2010). Farmers should be equipped with the necessary information and resources to accurately analyze costs and returns when investing in technology. The selection of cost-effective technologies is critical for the sustainability of the agricultural economy (Mutenje et al. 2019). Beyond sustaining the agricultural economy, economic factors are also closely tied to environmental sustainability. Cost-effective technologies that reduce input use, such as water-saving systems or energy-efficient practices, can simultaneously increase financial returns and contribute to environmental protection (Lakhiar et al. 2024). This interplay underscores the importance of strategies that address both economic and environmental sustainability. Additionally, conducting cost-effectiveness analyses for farmers is essential. Technologies with a high return on investment should be encouraged, and long-term financial support should be provided. Developing robust financial support mechanisms for agricultural technology investments is vital to fostering adoption and ensuring sustainability.

Environmental sustainability (0.137) is the fourth most important criterion. This criterion encompasses environmental factors such as energy efficiency, carbon footprint, and water conservation. Environmental sustainability ensures that agricultural activities are conducted in a manner that preserves the environment, supporting the long-term viability of agricultural production (Raji et al. 2024). Environmental sustainability is closely linked to technological suitability. Technologies designed to reduce carbon footprints or conserve water are highly effective in achieving environmental sustainability (Sizirici et al. 2021). However, the success of these technologies depends on social acceptance and user satisfaction (Öztaş Karlı et al. 2022). To maximize their impact, the adoption of energy-efficient technologies should be encouraged, and the use of renewable energy sources in agriculture should be expanded. Additionally, practices aimed at reducing carbon footprints should be widely adopted, and environmental impacts should be continuously monitored. The implementation of water-saving irrigation systems should be increased, and effective management of water resources must be ensured. These efforts are essential for balancing productivity with environmental stewardship, ultimately contributing to a more sustainable agricultural future.

The fifth main criterion is social and user satisfaction (0.119). This criterion reflects the level of acceptance and satisfaction with technologies by users. Social acceptance and user satisfaction are critical for the sustainable use of technologies (Castiblanco Jimenez et al. 2021). This criterion ensures that agricultural technologies are adopted and used effectively by users (Gabriel & Gandorfer, 2023). Social acceptance is directly linked to ease of use, which is a sub-criterion under technological suitability. Farmers are more likely to adopt technologies with user-friendly interfaces (Schwering et al. 2022). On the other hand, this criterion also affects the economic factors criterion. The lower the level of user satisfaction, the less likely people are to invest in these technologies (Makarem et al. 2009). For this reason, the agricultural technologies that emerge should both meet user expectations and achieve economic objectives. At the same time, training programs and awareness-raising activities should be carried out to increase the social acceptance of agricultural technologies. Interactive training programs should be organized, especially considering the needs of farmers. For example, farmers can have hands-on learning experiences with modular training programs focusing on specific technologies such as smart irrigation systems. These experiences can accelerate the adoption process of farmers by increasing their confidence and knowledge of the technology. Community participation is very important in the process of acceptance and adoption of new technologies (Wang et al. 2012; Marimuthu et al. 2022). Considering farmers' views on the technologies they will use will increase empowerment and ownership, as well as facilitate the customization of these technologies to regional and cultural conditions.

The main criterion with the lowest importance is political and administrative factors (0.108). Administrative factors, such as regulatory harmonization and supportive policies, are assessed under this criterion. Political and administrative factors refer to the legal and managerial framework necessary for the applicability and sustainability of agricultural technologies. The healthy functioning of these factors ensures the dissemination and effective use of agricultural technologies (Tey & Brindal 2012; Kuhlmann 2015). Political and administrative factors interact with environmental sustainability and social acceptance. Policies that encourage or incentivize the use of renewable energy or carbon footprint reduction can directly affect environmental performance. In addition, supportive policies that make agricultural technologies more accessible and affordable can increase social acceptance among farmers (Barnes et al. 2019). However, regional and cultural differences affect the perception and implementation of these policies by farmers (Prokopy et al. 2015). Furthermore, different government interventions and policies need to be adopted in regions with developed agricultural policies and regions with less developed governance systems. At this point, state support and incentives should be provided, taking regional and cultural differences into account in the dissemination process of agricultural technologies. Additionally, while developing agricultural technology policies, more inclusive and effective strategies should be created in cooperation with stakeholders.

When the sub-criteria are evaluated, innovation (0.419) under the main criterion of technological relevance is seen as the most important sub-criterion. Innovation enables the application of modern and efficient methods in agricultural production and increases competitiveness (Cornejo-Velazquez et al. 2022). In smart villages, it is necessary to adopt innovative agricultural technologies, continuously follow technological developments and produce innovative solutions. The second important sub-criterion is ease of use (0.323). Ease of use is critical for the adoption and effective use of technologies (Castiblanco Jimenez et al. 2021). At this point, it is important to design agricultural technologies with user-friendly interfaces and increase training for farmers. Compatibility (0.258) is the third important sub-criterion. Compatible technologies increase productivity by integrating with existing systems (Gabriel & Gandorfer 2023). It is necessary to select technologies that are compatible with existing farming systems and to facilitate the integration process.

Yield increase (0.433) is the most important sub-criterion under the main criterion of Productivity and Performance. Yield increase increases farmers' incomes by increasing production capacity (Balafoutis et al. 2020). Technology investments to increase productivity in agriculture should be encouraged and performance indicators that monitor productivity should be established. The second important sub-criterion is time savings (0.320). Time saving enables agricultural activities to be carried out faster and more efficiently (Elijah et al. 2018). It is important to adopt time-saving automation and mechanization solutions. Precision (0.247) is the third important sub-criterion. Precision agriculture enables more efficient use of resources and reduces waste (Karunathilake et al. 2023). By increasing the use of precision agriculture techniques, more efficient use of inputs should be ensured.

Cost effectiveness (0.427) is the most important sub-criterion under the main criterion of economic factors. Cost-effective technologies increase the competitiveness of farmers by reducing their production costs (Raji et al. 2024). The selection of cost-effective technologies is critical for the sustainability of the agricultural economy. Cost-effectiveness analyses should be conducted for farmers. The second important sub-criterion is return on investment (0.329). High return on investment accelerates the return on farmers' investments in technology (Yigezu et al. 2018). Technologies that provide high return on investment should be promoted and long-term financial support should be provided. Financial Support (0.244) is the third important sub-criterion. Financial support facilitates farmers' adoption of new technologies (Amadu et al. 2020). It is important to develop financial support mechanisms for agricultural technology investments.

Energy efficiency (0.433) is the most important sub-criterion under the main criterion of Environmental Sustainability. Energy efficiency reduces environmental impacts by reducing energy costs (Engler & Krarti 2021). The use of energy efficient technologies should be encouraged. The use of renewable energy sources in agriculture should be increased. Carbon footprint (0.320) is the second important sub-criterion. Carbon footprint reflects the environmental impacts of agricultural activities and it is important to reduce it (Adewale et al. 2019). Practices to reduce carbon footprint should be adopted and environmental impacts should be continuously monitored. The third important sub-criterion is water conservation (0.247). Water conservation ensures sustainable use of water resources (Gobarah et al. 2015). The use of water-saving irrigation systems should be increased and effective management of water resources should be ensured.

Accetance (0.406) is the most important sub-criterion under the main criterion of social and user satisfaction. Acceptance ensures that technologies are adopted and used effectively by the society (Castiblanco Jimenez et al. 2021). In order to increase social acceptance of agricultural technologies, awareness raising activities should be carried out in the community. The second important sub-criterion is health and safety (0.324). Health and safety are critical for the protection of agricultural workers and consumers (Baran & Ersoy Karaçuha 2021). The use of technologies that comply with health and safety standards should be encouraged. Education and information (0.270) are the third important sub-criterion. Training and information enable farmers to use new technologies more effectively (Sennuga & Oyewole 2020). Continuous training and information programs should be organized for farmers.

Regulatory compliance (0.419) is the most important sub-criterion under the main criterion of political and administrative factors. Regulatory compliance ensures that agricultural technologies comply with the legal framework (Kuhlmann 2015). It is necessary to ensure the compliance of agricultural technologies with the legislation and to make the necessary regulations. Supportive policies (0.323) are the second important sub-criterion. Supportive policies encourage the diffusion and adoption of technologies (Tey & Brindal 2012). Policies that support the diffusion of agricultural technologies should be developed. The third important sub-criterion is administrative facilities (0.258). Administrative facilities increase the availability of technologies (Ntaliani et al. 2010). Administrative arrangements should be made to facilitate the use of technology.

The sensitivity analysis and Kendall's Coefficient of Concordance further enhance the robustness of the study's findings. While the sensitivity analysis reveals that the evaluation process is reliable, it also shows that the results are not highly dependent on small changes in weight assignments. Similarly, the Kendall value (0.85) validates the weight assignments by indicating a high level of agreement among the experts. The combination of these two methods increases the robustness and reliability of the evaluation framework used in the study.

Moreover, the findings provide insights that can be applied in different sectors. For example, the appropriate criteria (e.g., Technological Relevance, Economic Factors, Political and Governance Factors) and sub-criteria (e.g., Ease of Use, Innovativeness, Acceptance) can be used in the selection of telemedicine technologies in the health sector or digital learning platforms in the education sector. The SWARA method can be adjusted to sector-specific objectives, facilitating informed decision-making across a wide range of sectors. This adaptability ensures that the contributions of the study extend beyond the agricultural sector, promoting sustainable and efficient practices globally.

6. Conclusions

This study presents a comprehensive assessment of agricultural technologies for smart villages using the SWARA method and emphasizes the importance of criteria such as technological relevance, efficiency, and economic factors. Sub-criteria such as innovation, yield increase, and cost-effectiveness are identified as critical factors in decision-making.

The robustness of the findings is confirmed by a sensitivity analysis, which demonstrates stability in the criteria rankings under ±10% and ±20% weight changes. Furthermore, Kendall's Coefficient of Concordance (0.85) validates the reliability of the evaluation framework by highlighting a strong consensus among the experts.

This study underscores the effectiveness of the SWARA method as a structured and flexible tool for assessing agricultural technologies compared to other methods, offering a novel perspective that contributes to the sustainable and efficient management of smart villages.

The findings suggest feasible strategies for policymakers and stakeholders, such as prioritizing user-friendly and cost-effective technologies, providing financial incentives such as subsidies for smart irrigation systems, and investing in sustainability-oriented initiatives. These contributions align local agricultural needs with global sustainability goals such as Zero Hunger (SDG 2), Decent Work and Economic Growth (SDG 8), and Responsible Consumption and Production (SDG 12).

Future studies should explore the integration of SWARA with other MCDM methods to enhance flexibility and validate these findings in real-world applications. This study provides a robust framework, paving the way for more effective agricultural practices and broader applications in other sectors, such as rural healthcare and education.

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