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Evaluation of Mobile Applications for Small Farms Using Fuzzy Methods

Adis Puška[1], Anđelka Štilić[2], Miroslav Nedeljković[3], Darko Božanić[4], Dragan Pamučar [5,6,*]

[1] Government of Brčko District, Department of Public Safety, Brčko, Bosnia and Herzegovina; adispuska@yahoo.com;
[2] Academy of Applied Studies Belgrade, College of Tourism, Belgrade, Serbia; andjelka.stilic@gmail.com;
[3] Institute of Agricultural Economics, Belgrade, Serbia; miroslavnedeljkovic2015@gmail.com;
[4] Military Academy, University of Defence in Belgrade, Belgrade, Serbia; dbozanic@yahoo.com;
[5] Széchenyi István University, Győr, Hungary;
[6] Department of Applied Mathematical Science, College of Science and Technology, Korea University, Sejong 30019, Republic of Korea ; dpamucar@gmail.com;

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Abstract

This paper offers a practical model to help farmers choose the most suitable mobile application for their specific needs, improving decision-making processes in adopting agricultural technology. Given the wide range of applications available on the market, the need to select the one that best improves agricultural production motivated the research in this paper. To simplify the decision-making process for farmers, a methodology that applied the fuzzy approach was developed. Based on this, this research aimed to evaluate and identify mobile applications most suitable for the Farmino farm using a multi-criteria decision-making approach. A decision-making model that includes ten criteria and several mobile applications was applied. Farm employees, who are the intended users of these applications, evaluated the criteria and applications using linguistic terms. The methods of fuzzy SiWeC (Simple Weight Calculation) and fuzzy LOPCOW (Logarithmic Percentage Change-Driven Objective Weighting) were used to determine the weight of the criteria. These methods revealed that the criterion "Data accuracy" was more important than the others, while the importance of the other criteria was less. Finally, the fuzzy method MABAC (Multi-Attributive Border Approximation Area Comparison) was used to rank mobile applications, and the results showed that the A4 mobile application ranked highest, making it the best choice for Farmino Farm.

Keywords: mobile applications, small farms, fuzzy methods, multi-criteria decision-making.

Corresponding Author: dragan.pamucar@fon.bg.ac.rs

1|Introduction

Technological progress and innovations have influenced how business is conducted across industries, including agriculture. The increasing use of innovative technologies has driven the digitalization of farms, with more creative solutions being adopted (Shostak et al., 2024). Mobile devices, in particular, allow users to access applications anytime and anywhere (Emeana et al., 2020), making them a central tool for managing various agricultural systems. Many agricultural technologies can now be accessed through mobile devices (Ullah et al., 2024), positioning mobile applications as key tools in supporting farms' efficient and organized operation (Karar et al., 2021).

Small farms, however, face unique challenges due to limited resources and labor (Giller et al., 2021). Financial limitations often restrict their access to advanced equipment and technologies, putting them at a disadvantage compared to large agricultural systems (Benyam et al., 2021). This lack of resources prevents small farms from investing in employee training or adopting sophisticated tools to improve productivity. As a result, small farms are particularly vulnerable to changing market conditions and climatic events, making it harder to maintain stable operations. In this context, mobile applications offer a practical solution to enhance efficiency, optimize resource use, and reduce operating costs for small farms (Javaid et al., 2023) while improving competitiveness (Škuflić et al., 2024).

Mobile applications have become increasingly important in daily agricultural work (Emeana et al., 2020), providing tools for better planning, management, and monitoring of key farm activities. These applications offer a range of options, including weather monitoring (Pajić et al., 2024), stock management, production tracking, crop and livestock health monitoring, and data analysis to support decision-making. Mobile applications simplify everyday tasks for small farms, saving time and reducing costs. Past organizational and planning benefits, these tools also enhance communication between farmers, suppliers, buyers, and other supply chain participants (Nguyen et al., 2024). For example, inventory management applications help farmers efficiently plan purchases, avoid delays, and reduce costs (Tripathi et al., 2023). These tools also minimize resource wastage and enable better financial management by simplifying cash flow.

Despite these advantages, not all mobile applications are equally fitted to the specific needs of small farms (Mizik, 2021). To identify the most appropriate applications, it is necessary to compare their features and evaluate how well they address the unique needs of small-scale farming. Careful evaluation can help farmers select applications that are accessible, user-friendly, and functionally relevant to their operations, minimizing the risk of adopting ineffective tools.

To select the mobile application best suited to its needs, the Farmino farm requires a structured model for evaluating and comparing available alternatives. This research uses fuzzy decision-making methods, which allow the review of numerous aspects and criteria. The fuzzy approach is particularly suited for evaluating mobile applications because it adapts qualitative and quantitative criteria using linguistic values, simplifying decision-making. That enables a data-driven approach, reducing the risk of unsuccessful application selection.

The importance of using fuzzy methods is seen in the fact that sometimes the decision-maker does not have complete information and must make an incomplete decision. Then, the decision-maker cannot give an exact score but uses linguistic concepts to provide an approximate score in this case of criteria and applications. To use these scores, a fuzzy approach that converts these scores into fuzzy numbers (Biswas et al., 2024; Khalifa, 2024) is applied to perform mathematical operations further (Barati et al., 2024) that will contribute to establishing criteria importance and ranking alternatives (Chabok & Tešić, 2024). Besides, this paper considered applications according to numerous criteria, making it necessary to use multi-criteria analysis methods. These methods allow for assessing the importance of criteria and how the alternatives, in this case, applications, meet these criteria.

This research is motivated by the need for small farms to have reliable digital tools to improve efficiency and productivity. With many applications available on the market, choosing the right one can be challenging without proper analysis. By applying fuzzy decision-making methods, this study aims to provide practical and scientifically validated solutions to address the specific challenges that small farms face.

The challenges faced in this research, which distinguish it from similar studies, are the following:

- Small farms are increasingly using innovative technologies. These technologies are increasingly affordable (Giller et al., 2021) and suitable for small farms, helping them improve their businesses (Emeana et al., 2020).
- Many small farms are using applications to improve their businesses. Applications have become necessary for implementing smart technologies on farms (Pajić et al., 2024) as they collect the data needed for decision-making (Javaid et al., 2023).
- More and more applications on the market specialize in small farms. They differ in their capabilities (Karar et al., 2021). Therefore, it is necessary to choose a specific application to help manage a small farm (Tripathi et al., 2023).

To address these challenges, this research was conducted. The objective is to identify a mobile application that most effectively serves the needs of the Farmino farm through a fuzzy approach. With this aim, a decision-making model will be developed, and the fuzzy method will be used. The specific objectives include:

- Identify key criteria for evaluating mobile applications for small farms. Applying this objective, we will determine which options in the application are more important for practical application on the Farmino farm.
- Apply a fuzzy approach to evaluating mobile applications. This allows for decision-making in situations where there is uncertainty.
- Compare and rank mobile applications to make an informed final decision. This process will select a specific application that could best improve the operation of the Farmino farm.
- Provide recommendations for selecting mobile applications that increase the efficiency and productivity of small farms. Based on these recommendations, selecting a specific application for other small farms in practical applications is possible.
- Identify critical application features to guide improvements to existing applications or encourage the development of new ones. The results of this research will show in which direction developers should move to make their applications more desirable for small farms.

When selecting an application for a small business, deciding which is most suitable for users is necessary. Therefore, it is important to select the application that is the best fit according to the users. However, to choose one application, it is necessary to compare it with other applications. This decision-making problem is even more specific because there are many applications on the market, so this research helps in this choice. The paper`s contributions are based on:

- Developing a fuzzy-based model for evaluating mobile applications tailored to small farms.
- Assisting small farmers in making informed decisions when selecting farm management applications.
- Contributing to the development of future mobile applications by identifying features important for small farms.
- Promoting the use of mobile applications in agriculture to enhance competitiveness and sustainability for small farms.

Additionally, the paper aims to provide guidelines for further research integrating fuzzy approaches with agricultural technology to improve operations on small farms.

2 | Literature review

The literature review will examine the role of applications in modern agricultural production and the associated technologies, enabling farmers to access essential information. It will also explain how mobile applications improve this production and how decisions are made using them. At the end of this section, the reasons why MCDM methods are used in the application selection and their role will be explained. References to previous research will support all of this.

The growing integration of mobile applications in agriculture has revolutionized farming practices worldwide (Sharma et al., 2022), addressing efficiency, sustainability, and productivity challenges. The rise of artificial intelligence (AI) (Abdelhafeez & Aziz, 2024) and the Internet of Things (IoT) has driven the development of sophisticated mobile applications tailored to agriculture (Sasmal et al., 2024). For instance, AI-SHES, a smart hydroponics expert system, uses IoT devices and deep-learning modeling for predicting nutrients, detecting plant disease, and automated control systems (Rutendo Magwedere & Marozva, 2025; Raju et al., 2022). Farmers can access real-time sensor data and disease diagnostics through mobile applications, enabling them to track crop health and optimize productivity. This system demonstrates high accuracy in disease classification and offers a scalable solution for hydroponic farming (Raju et al., 2022).

Beyond hydroponics, the broader adoption of smart technologies such as real-time data analysis, precision farming tools, and advanced monitoring systems has shown great potential when faced with problems like the effects of global warming, labor shortages, and market unpredictability (Maring et al., 2023). However, while much of the research has focused on large-scale agricultural systems, small farms, limited by financial resources and technical support, often struggle to adopt these innovations. This highlights an urgent need for technologies that are cost-effective, user-friendly, and adaptable to the unique operational contexts of small farms.

Integrating IoT and AI, mobile robotics represents another leap in precision farming, optimizing resource use and reducing environmental impact (Phasinam et al., 2022). Despite the potential for autonomous and cost-effective farming, challenges remain in connectivity, affordability, and implementation for small farms (Yépez-Ponce et al., 2023).

Mobile applications impact farm-level decision-making and efficiency (Sivakumar et al., 2022), offering solutions for resource management, crop monitoring, and supply chain optimization. For instance, Australian livestock farmers expressed enthusiasm for mobile applications that enable informed decisions, improve efficiency, and simplify information management. However, adopting agricultural applications lags behind general application use due to a perceived lack of relevant and user-friendly options. This highlights the importance of designing applications that align with farmers' operational needs and resource limitations (Schulz et al., 2021). Applications for soil analysis, weather forecasting, and crop monitoring can significantly lower costs and save time (Mössinger et al., 2021). Similarly, a study in Sarawak, Malaysia, explored the goal of implementing e-AgriFinance. Expectations of performance, effort, and social influence played significant roles in the adoption process. Interestingly, perceived cost, contrary to expectations, positively influenced behavioral intention, indicating the perceived value of digital solutions among farmers (Omar et al., 2021).

Evaluating mobile applications tailored to specific farming contexts is crucial for their effective adoption. Criteria such as ease of use, data accuracy, compatibility, and cost-effectiveness are often assessed using expert judgment or user feedback. Multi-criteria decision-making (MCDM) models and fuzzy methodologies offer structured approaches to evaluating these applications, mainly when dealing with uncertainties (Duc Trung et al., 2024; Abid et al., 2025). These approaches balance qualitative and quantitative factors, making them ideal for addressing the diverse needs of small farms (Räty et al., 2023; Kumar, 2024).

For example, fuzzy MCDM models have been used to optimize resource allocation (Nezhad et al., 2023; Biswas S. et al., 2024), evaluate farming equipment (Puška et al., 2022), and assess supply chain risks (Amin et al., 2022). These models have the potential to evaluate mobile applications, considering factors like cost and user adaptability, and could help bridge the gap between technical innovation and practical usability for small-scale farmers.

Mobile applications are also a key part in enhancing market access, especially in developing regions (Khan et al., 2022). For example, an application in Thailand supports elderly farmers by optimizing marketing and logistics using location-based tools based on algorithms such as Dijkstra's and Ant Colony to achieve high accuracy rates in route optimization, improving supply chain efficiency. This model exemplifies how mobile applications empower marginalized groups to participate effectively in agricultural economies (Nuanmeesri, 2019). In Nigeria, mobile phones have enabled communication and skill enhancement, benefiting rural farmers' livelihoods. This reflects a global trend in leveraging mobile phones to access agricultural information, financial services, and output markets, particularly in remote areas (Baumüller, 2022). However, barriers such as language, technical skills, and awareness remain significant, underscoring the need for capacity-building policies (Anadozie et al., 2022; Ali et al., 2024). Similarly, in South Africa, mobile applications have improved smallholder productivity and food security, though challenges persist in infrastructure and technical literacy, calling for government intervention (Mdoda et al., 2023).

The adoption of mobile technology in agriculture varies across regions and demographics. A systematic review of mobile phone technology adoption identifies key determinants such as education, gender, perceived ease of use, and cost. On the other hand, limitations like inadequate infrastructure and language barriers are noticeable in developing regions. Many services rely on SMS and voice-based interfaces to cater to low-tech phones, limiting their sophistication and potential to support advanced agricultural practices (Baumüller, 2022). Standardized approaches to assessing adoption metrics and using behavioral theories are essential for scaling adoption effectively (Aparo et al., 2022).

While mobile applications primarily target large-scale agricultural systems, small farms face unique challenges, including limited financial resources, technical training, and employee capacity (Mizik, 2022). This highlights the need for inclusive research and development of mobile tools that align with small farms' operational realities. Due to their accessibility and affordability, mobile applications hold a promise in addressing these challenges.

3 | Methodology and research methods

The section of a mobile application in this research will be conducted through the following phases:

- Phase 1. Formation of the research model
- Phase 2. Evaluation of the elements of the research model
- Phase 3. Application of fuzzy research methods
- Phase 4. Conducting additional analyses

Initially, defining the practical case for this research enables the development of a decision-making model (Yazdi and Komasi, 2024; Elraaid et al., 2024), and this specific research is carried out for the Farmino farm, which is situated in Brčko District`s southern part of the Brčko District, in Bosnia and Herzegovina (BiH). Part of the Posavina region, the Brčko District is an administrative area in northeastern BiH with the biggest lowland area, well-known for its agricultural potential and numerous rural activities.

The Farmino farm is a small family farm that grows strawberries. The farm uses greenhouses to grow the strawberries, helping reduce the effects of changing weather. Each greenhouse has an irrigation system that provides water for the plants. The farm is working to improve its production by adding sensors to collect information about fertilizer needs. A small drone is being considered for purchase to help with mapping the fields, monitoring plant health, improving irrigation, and applying pesticides and fertilizers. This will give the farmers important information about the condition of the strawberries. There are also plans to automate the irrigation system to make it easier to control.

To manage all these systems, the farm needs a mobile application. Mobile applications are a good choice because they allow farmers to access the necessary information from anywhere. Three farmers are currently working on this farm, and they will also participate in this research as users of the application.

A total of ten mobile applications were selected as alternatives for this research. The selection was based on the condition that the price of each application does not exceed 200 euros per year to ensure costs are controlled. These applications are designed for small farms and were chosen after searching online and checking specialized agricultural websites. With the idea of preserving fairness, the names of the applications are not included, and they are instead labeled as Applications 1 through 10. The application names were deliberately left out to avoid promoting a specific company. However, this approach acknowledges that what works best can vary from one farm to another. In addition, mentioning specific application names could unfairly promote some while disadvantaging others, which is why this decision was made.

The features of each application are described below:

- Application 1 (A1): This application tracks farm yields, weather conditions, land analysis, costs, and helps organize everyday farm tasks.
- Application 2 (A2): This application focuses on recording farm activities through a digital diary. It includes tools for mapping land, analyzing soil, and tracking yields. It works on both Android and iOS and is made for smaller farms.
- Application 3 (A3): This application uses weather and satellite data to predict farm yields, helping farmers plan their work.
- Application 4 (A4): This application provides information about field conditions, yields, and watering schedules. It helps farmers plan planting and harvesting by comparing past and current data.
- Application 5 (A5): This application offers tools for managing farms, including tracking crops and animals. Farmers can use this application to plan better and save on costs.
- Application 6 (A6): This application advises farmers on soil care, crop protection, and watering. It is free to use, making it easy for small farms to access.
- Application 7 (A7): This application shares local weather forecasts and sends alerts about weather changes. It is useful for farms that depend on accurate weather information.
- Application 8 (A8): This application helps manage resources and monitor animal health. It supports decisions about soil, crops, and animals.
- Application 9 (A9): This application tracks weather data and yields, helping farmers make decisions based on past weather patterns. It is designed for small farms.
- Application 10 (A10): Monitors crops, analyzes soil, and helps manage watering. It is focused on cutting costs and using resources wisely on farms.

To compare the selected applications, ten criteria were chosen, as outlined below:

- Ease of use (C1): Applications should be simple and intuitive, especially for users with limited technology experience. This makes it easier for farmers to adopt and use the applications in their daily activities.
- Multi-language support (C2): Since these applications are used globally, they should include multiple language options to be more accessible and user-friendly. This is particularly important for agricultural technologies in diverse regions.

- Offline functionality (C3): Farmers often work in areas with limited internet access. Applications need to function offline to allow continuous data collection and processing even in remote locations.
- Application affordability (C4): Cost is critical for small farms. Applications that offer affordable pricing or flexible payment options are more likely to be used by farmers.
- Notification functionality (C5): Applications should provide timely alerts about key farming activities such as irrigation schedules or weather updates. This helps farmers respond quickly to changing conditions.
- Data accuracy (C6): Reliable and up-to-date information about weather, soil conditions, and other key factors is essential for effective farm decision-making.
- Monitoring and reporting (C7): Applications should support monitoring crops and animals while generating reports to help farmers manage their resources efficiently.
- Interoperability (C8): Applications should connect easily with sensors and other devices to gather accurate data. This feature is especially useful for modern farms using various technologies.
- Data security (C9): Protecting the confidentiality of farm data is crucial. Applications should include strong security measures to ensure safe use.
- Personalization (C10): The ability to customize applications based on specific farm needs makes them more useful. Flexibility in adapting features can help optimize farming activities.

The research model was established by selecting these criteria and the ten application alternatives. The next phase evaluates the importance of each criterion and how well applications meet them. Since the criteria are qualitative, they will be assessed using linguistic terms such as "very poor" to "absolutely high." These terms simplify the evaluation process for users. Both criteria and alternatives will be rated using the same scale for consistency.

Linguistic terms	Triangular fuzzy numbers
very poor (vp)	(1, 1, 2)
poor (p)	(1, 2, 3)
medium poor (mp)	(2, 3, 4)
medium (m)	(3, 4, 5)
medium high (mh)	(4, 5, 6)
high (h)	(5, 6, 7)
very high (vh)	(6, 7, 8)
extremely high (eh)	(7, 8, 9)
absolutely high (ah)	(8, 9, 9)

Table 1. Use of linguistic terms

After users evaluate the criteria and alternatives, fuzzy methods are applied to calculate the criteria's importance and rank alternatives based on how effectively they meet the criteria. To use these methods, linguistic terms must first be converted to fuzzy numbers. The conversion is done by a membership function, which assigns values to triangular fuzzy numbers. The process begins by evaluating the criteria and alternatives using linguistic terms, followed by their conversion into fuzzy numbers.

Three fuzzy methods will be used in this research: fuzzy SiWeC (Simple Weight Calculation), fuzzy LOPCOW (Logarithmic Percentage Change-Driven Objective Weighting), and fuzzy MABAC (Multi-Attributive Border Approximation Area Comparison). Fuzzy SiWeC and fuzzy LOPCOW will determine the criteria weights, as the SiWeC determines weights using users' subjective criteria evaluations, and the LOPCOW method calculates weights objectively, using evaluations of alternatives provided by the users. Combining the results of these two methods reduces the user`s subjectivity effect on the final weights, as final criteria weights will result from both subjective and objective evaluations. In addition, these two methods for determining criteria weight provide decision-making reliability since decision-makers can access diverse criteria and be more confident in making a decision. In this way, they do not rely solely on their judgment but also introduce a certain amount of objectivity into the decision. For this reason, a combination of methodologies is used in the analysis, with fuzzy MABAC (Chen et al., 2025) ranking the applications according to how well they meet the criteria in the end. The following is a brief explanation of each method.

The fuzzy SiWeC method (Puška et al., 2024) uses expert evaluations for individual criteria. There are several reasons for using this method. Firstly, this method is newer and needs to be implemented in practice, which is why it is promoted in this research. Secondly, this method does not require that the criteria be compared or ranked, but it is enough to assess the criteria in terms of importance. Thirdly, unlike other methods for weight determination, this method makes a difference in the assessments of experts, and therefore, differently influences the final decision. These are just some reasons why this method was used over other methods for weight determination. The steps (S 1-7) involved in this method are:

S 1. Determination of the importance of the criteria.

S 2. Converting linguistic values.

S 3. Normalizing the fuzzy numbers using:

$$\tilde{n}_{ij} = \frac{x_{ij}^{l}}{max\ x_{ij}^{u}}, \frac{x_{ij}^{m}}{max\ x_{ij}^{u}}, \frac{x_{ij}^{u}}{max\ x_{ij}^{u}} \tag{1}$$

Here, $max\ x_{ij}^{u}$ represents the maximum criterion value among alternatives.

S 4. Calculating the standard deviation of the ratings provided by the experts ($st.dev_j$).

S 5. Normalizing the ratings by incorporating the standard deviation:

$$\tilde{v}_{ij} = \tilde{n}_{ij} \times st.dev_j \tag{2}$$

S 6. Summing the criteria weights:

$$\tilde{s}_{ij} = \sum_{j=1}^{n} \tilde{v}_j \tag{3}$$

S 7. Calculating criteria fuzzy weights:

$$\widetilde{w}_{ij} = \frac{s_{ij}^{l}}{\sum_{j=1}^{n} s_{ij}^{u}}, \frac{s_{ij}^{m}}{\sum_{j=1}^{n} s_{ij}^{m}}, \frac{s_{ij}^{u}}{\sum_{j=1}^{n} s_{ij}^{l}} \tag{4}$$

The fuzzy LOPCOW method was developed by Ecer & Pamučar (2022). Like the fuzzy SiWeC method, the fuzzy LOPCOW is a newer one used for criteria weight determination, and its application is promoted in this research. However, it uses the initial decision matrix and methods to determine the order of alternatives. Another explanation for why this method was chosen is that it uses the same normalization as fuzzy MABAC. In addition, it has a smaller number of steps compared to other similar methods. The steps (S 1-9) include:

S 1. Evaluates alternatives.

S 2. Converts linguistic values.

S 3. Creates the initial fuzzy decision-matrix

S 4. Normalizes the fuzzy decision-matrix using:

$$\tilde{r}_{ij} = \left(\frac{x_{ij}^{l} - x_{i\,min}^{l}}{x_{i\,max}^{n} - x_{i\,min}^{l}}; \frac{x_{ij}^{m} - x_{i\,min}^{l}}{x_{i\,max}^{n} - x_{i\,min}^{l}}; \frac{x_{ij}^{n} - x_{i\,min}^{l}}{x_{i\,max}^{n} - x_{i\,min}^{l}} \right) \tag{5}$$

Where $x_{i\,max}^{n}$ is the maximum value for criterion at n-th fuzzy number, $x_{i\,min}^{l}$ minimum value for criterion at l-th fuzzy number.

S 5. Calculates the criteria percentage value (PV) using:

$$\widetilde{PV}_{ij} = \left| \ln\left(\frac{\sqrt{(\sum_{i=1}^{m} r_{ij}^{2})/m}}{\sigma} \right) \cdot 100 \right| \tag{6}$$

Where Ln stands for natural logarithm, and σ for standard deviation

S 6. Determines weights using:

$$\widetilde{w}_j = \frac{\widetilde{PV}_{ij}}{\sum_{i=1}^{n} \widetilde{PV}_{ij}} \tag{7}$$

The fuzzy MABAC method (Pamučar and Ćirović, 2015) follows steps 1 to 4 from fuzzy LOPCOW, but with additional steps (S 5 – 9) to rank alternatives.

S5. Calculates a weighted matrix using:

$$\tilde{v}_{ij} = w_i \cdot \tilde{t}_{ij} + w_i \tag{8}$$

S 6. Determines the border area matrix.

$$\tilde{g} = \left(\prod_{j=1}^{m} \tilde{v}_{ij}\right)^{1/m} \tag{9}$$

S 7. Calculates deviation from the approximate border area.

$$\tilde{Q} = \tilde{V} - \tilde{G} \tag{10}$$

S 8. Calculates MABAC value.

$$\tilde{S}_i = \sum_{j=1}^{n} \tilde{q}_{ij}\ , \ j = 1,2, \dots, n, i = 1,2, \dots, m \tag{11}$$

S 9. Calculates the final value of the MABAC method.

$$S = \frac{t_1 + 4t_2 + t_3}{6} \tag{12}$$

The optimal alternative is identified as the one that results in the highest final value.

After the ranking order of observed mobile applications for small farms is determined, additional analyses are performed in comparative analysis and sensitivity analysis. A comparative analysis is done by applying identical weights while implementing different fuzzy output methods. Therefore, in this research, fuzzy versions of the following methods will be used for this analysis: MARCOS (Measurement of Alternatives and Ranking according to the Compromise Solution), WASPAS (weighted aggregated sum product assessment), SAW (Simple Additive Weighting), RAWEC (Ranking of Alternatives with Weights of Criterion), and ARAS (Additive Ratio ASsessment). The fuzzy MARCOS got selected due to its ability to rank alternatives by considering both ideal and anti-ideal points, and utility functions are formed on this basis (Shahid et al., 2023). This method uses another type of normalization when compared to the fuzzy MABAC method. The fuzzy WASPAS integrates the results of the WSM (Weighted Sum Model) and the WPM (Weighted Product Model) (Khan et al., 2024) to establish a ranking based on the application of these methods. The fuzzy SAW represents the most straightforward method among multi-criteria analysis techniques. The ranking is determined by a total of weighted normalized values, making it appropriate for comparative analysis. The

RAWEC method has the specificity of using two normalizations (Petrović et al., 2024), which are variations of the same normalization, justifying its use in this analysis. The fuzzy ARAS applies an alternative normalization approach, with the ranking determined by the utility function relative to the optimal alternative.

Sensitivity analysis examines the influence of criteria weights on the final ranking. This analysis involves the creation of scenarios in which the weight of the criteria is modified and analyzing the impact of these changes on the final order. Sensitivity analysis can be performed through various methods. This study will use the initial weights of the criteria, with individual weights reduced by 90%. This will decrease the criterion's influence. The weights of the remaining criteria will be adjusted upwards in proportion to the reduction in the weight of this criterion. This process minimizes the impact of a specific criterion in ranking the alternatives.

4 | Results

The criteria weights must be determined to decide on a mobile application best suited for the Farmino farm. This is done by combining the fuzzy SiWeC and fuzzy LOPCOW methods. First, the weights are determined through the subjective criteria evaluation with the fuzzy SiWeC. This involves users assessing the importance of each criterion (Table 2) as a first step. This assessment relies on linguistic terms that are next converted to fuzzy numbers. A fuzzy decision matrix is created during this step through a membership function (Table 1). I.e., the linguistic term “absolutely high” or “ah” is converted to a fuzzy number (8, 9, 9).

Id	Criteria	User 1	User 2	User 3
C1	Ease of use	ah	vh	eh
C2	Multi-language support	eh	h	vh
C3	Offline functionality	vh	ah	h
C4	Application affordability	eh	eh	ah
C5	Notification functionality	h	vh	eh
C6	Data accuracy	ah	eh	ah
C7	Monitoring and reporting	vh	ah	eh
C8	Interoperability	h	eh	vh
C9	Data security	nh	h	vh
C10	Personalization capability	h	mh	eh

Table 2. Evaluation of criteria importance by application users

The initial decision matrix is normalized when all elements are divided by 9 (the highest fuzzy number value). The standard deviation of user ratings is then calculated to evaluate their importance. If users' ratings are more uniform, their influence is reduced compared to those with more varied ratings. The criteria values are then summed to determine the criteria weights.

Based on fuzzy SiWeC, C6 - Data accuracy (Table 4) was given the most weight. However, the other criteria weights did not differ significantly. Only C9 - Data security and C10 – Personalization showed slight deviations from the others, but these differences were not substantial. It can be concluded that, according to user ratings, all criteria are important when selecting a mobile application.

After determining the weights by fuzzy SiWeC, the weights are recalculated by fuzzy LOPCOW. The first four steps follow fuzzy MABAC methodology, and these steps are explained in the fuzzy LOPCOW. The first step involves alternatives evaluation (Table 3). Experts evaluate each application (Alternatives 1-10) relying on linguistic terms, which are then transformed into fuzzy numbers.

Table 3. Evaluation of alternatives by application users

User 1	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**
A 1	ah	mh	vh	h	eh	ah	ah	h	vh	vh
A 2	eh	h	eh	h	vh	vh	eh	vh	vh	vh
A 3	vh	m	h	mh	h	eh	vh	mh	h	mh
A 4	ah	mh	vh	vh	ah	ah	ah	eh	eh	vh
A 5	eh	mh	vh	vh	eh	eh	eh	h	vh	eh
A 6	vh	h	mh	eh	vh	h	mh	mh	h	h
A 7	vh	mh	h	vh	h	eh	h	mh	h	mh
A 8	ah	mh	vh	h	vh	ah	ah	eh	vh	vh
A 9	eh	mh	h	h	eh	ah	eh	eh	eh	vh
A 10	eh	m	h	vh	eh	eh	vh	h	vh	vh
User 2	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**
A 1	eh	mh	vh	vh	vh	ah	ah	h	vh	vh
A 2	eh	vh	eh	h	eh	vh	eh	vh	vh	eh
A 3	vh	m	h	mh	h	ah	vh	mh	h	mh
A 4	ah	mh	vh	h	ah	ah	ah	eh	eh	eh
A 5	eh	mh	vh	vh	vh	eh	ah	h	vh	eh
A 6	h	h	mh	eh	vh	h	mh	mh	h	h
A 7	vh	mh	vh	vh	vh	eh	h	mh	vh	mh
A 8	ah	mh	eh	h	eh	ah	ah	ah	eh	eh
A 9	eh	mh	vh	h	eh	ah	eh	ah	eh	vh
A 10	eh	m	h	vh	eh	eh	vh	h	vh	vh
User 3	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**
A 1	eh	mh	h	vh	vh	eh	ah	mh	h	h
A 2	eh	mh	eh	vh	vh	vh	vh	h	vh	h
A 3	h	m	mh	mh	mh	eh	vh	mh	h	mh
A 4	eh	mh	h	h	vh	eh	eh	vh	vh	h
A 5	eh	mh	vh	vh	vh	eh	eh	mh	h	eh
A 6	vh	h	mh	eh	h	h	mh	m	mh	h
A 7	vh	mh	vh	eh	h	eh	h	m	h	mh
A 8	eh	mh	vh	vh	h	eh	eh	vh	h	vh
A 9	vh	mh	h	h	vh	eh	eh	vh	vh	vh
A 10	vh	m	h	eh	vh	vh	h	mh	h	h

After linguistic transformation to fuzzy numbers, a summary fuzzy decision matrix is created by averaging user ratings. This ensures all users equally influence the decision-making process. The next step involves normalizing aggregated fuzzy decision matrix data by identifying the smallest and largest fuzzy values for each criterion and applying Expression 5 to calculate the normalized values. These normalized values are then scaled, and percentage values are calculated for determining weights via fuzzy LOPCOW (Table 4). Comparing the results from fuzzy LOPCOW and fuzzy SiWeC methods, it can be observed that the LOPCOW results are more unified, with weights for all criteria being relatively similar. Combining the weights from both methods to derive the final weights reduces the differences between the criteria. The results of fuzzy SiWeC have a greater influence on the final weights than the fuzzy LOPCOW.

	Fuzzy SiWeC	**Fuzzy LOPCOW**	**Product**	**Final weights**
C1	(0.09, 0.11, 0.14)	(0.08, 0.10, 0.12)	(0.01, 0.01, 0.02)	(0.05, 0.11, 0.24)
C2	(0.07, 0.10, 0.13)	(0.08, 0.10, 0.12)	(0.01, 0.01, 0.01)	(0.04, 0.10, 0.22)
C3	(0.08, 0.10, 0.13)	(0.09, 0.10, 0.11)	(0.01, 0.01, 0.01)	(0.05, 0.10, 0.22)
C4	(0.09, 0.11, 0.14)	(0.09, 0.10, 0.12)	(0.01, 0.01, 0.02)	(0.05, 0.11, 0.24)
C5	(0.07, 0.09, 0.12)	(0.09, 0.10, 0.12)	(0.01, 0.01, 0.01)	(0.04, 0.10, 0.22)
C6	(0.09, 0.12, 0.14)	(0.09, 0.10, 0.12)	(0.01, 0.01, 0.02)	(0.06, 0.12, 0.25)
C7	(0.09, 0.11, 0.14)	(0.09, 0.10, 0.11)	(0.01, 0.01, 0.02)	(0.05, 0.11, 0.23)
C8	(0.07, 0.10, 0.13)	(0.08, 0.09, 0.11)	(0.01, 0.01, 0.01)	(0.04, 0.09, 0.20)
C9	(0.06, 0.08, 0.11)	(0.09, 0.10, 0.12)	(0.01, 0.01, 0.01)	(0.04, 0.08, 0.19)
C10	(0.06, 0.08 ,0.11)	(0.09, 0.10, 0.11)	(0.01, 0.01, 0.01)	(0.04, 0.08, 0.19)

Table 4. Criteria weight values

After determining the criteria weights, the observed applications are ranked. After normalization, the next step is to calculate the weight matrix. This differs from traditional weighting methods, as the normalized values are multiplied by the weights and added to the weight values. Following this, the boundary area is determined, representing the geometric average of individual criteria from the weight matrix. The next step involves calculating the cumulative deviation from the boundary area. By performing defuzzification, the final values of fuzzy MABAC are obtained. Based on user evaluations, these results (Table 5) indicate the best-ranking mobile application as A4, followed by A8, and the worst performance is shown by A3.

	$\tilde{S}_i$	S_i	Rank
A1	(-3.27, 0.09, 3.42)	0.0822	6
A2	(-3.28, 0.07, 3.51)	0.0844	5
A3	(-3.40, -0.20, 2.89)	-0.2171	10
A4	(-3.23, 0.17, 3.56)	0.1666	1
A5	(-3.27, 0.08, 3.50)	0.0892	4
A6	(-3.39, -0.18, 2.96)	-0.1926	9
A7	(-3.35, -0.10, 3.11)	-0.1095	8
A8	(-3.24, 0.15, 3.54)	0.1470	2
A9	(-3.26, 0.10, 3.51)	0.1045	3
A10	(-3.32, -0.03, 3.28)	-0.0275	7

Table 5. Results of the fuzzy MABAC method

A comparative analysis was conducted to validate these results, as a growing number of current research efforts use comparative analysis (Božanić et al., 2024; Sarfraz, 2024; Kamran et al., 2024). According to some authors, it is an indispensable element of any multi-criteria decision-making model (Mishra et al., 2023; Jana and Islam, 2024). Results (Figure 1) show only fuzzy MABAC, which produces a ranking that differs slightly from other methods. This difference is in ranking the fourth-placed alternative, where applications A5 and A2 switch positions. This discrepancy arises because the fuzzy MABAC method employs a different normalization approach and does not use traditional weighting. Since the difference is limited to the fourth-placed alternative, it can be considered negligible, and the rankings of the other applications are confirmed. The analysis shows that using different methods in the research model for ranking applications was possible, and the same application would have been selected. This way, the decision-making model can be changed, which is a specific feature of applying fuzzy methods. It should be noted that each MCDM method uses appropriate steps that make it different from other methods (Vijayabalaji et al., 2024; Çalikoğlu & Łuczak, 2024). Therefore, it is necessary to model the decision and select methods that complement each other to facilitate the decision-making process. A sensitivity analysis is further conducted to assess the extent of deviations when the criteria weights are modified.

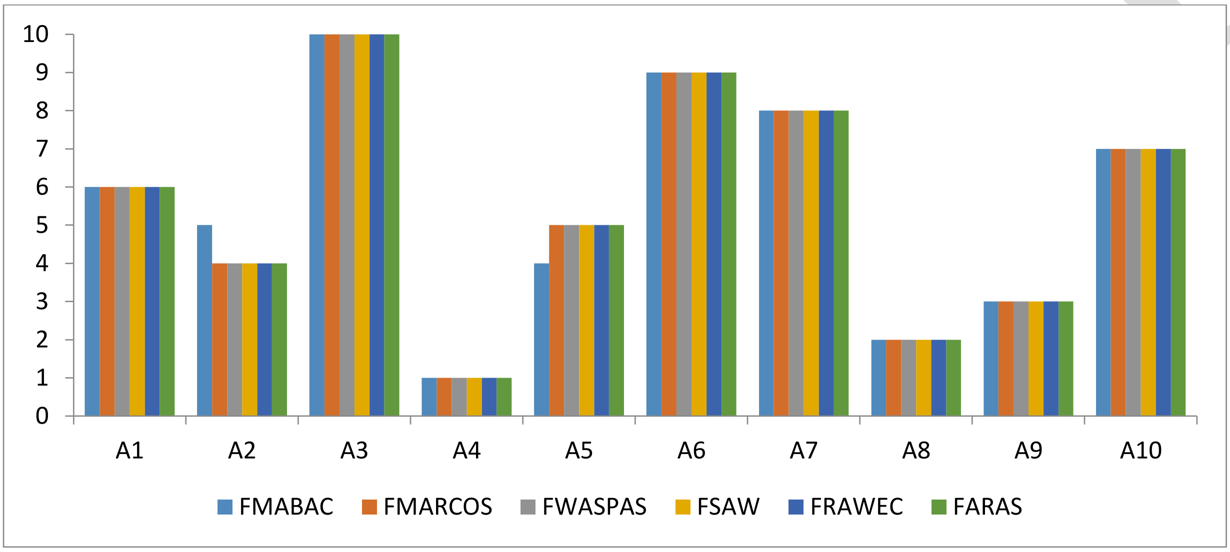

Fig. 1. Comparative analysis results

The next step in determining the quality of a model is sensitivity analysis. When combined with comparative analysis, sensitivity analysis provides a greater understanding of the quality of a given MCDM model (Tešić and Khalilzadeh, 2024; Więckowski and Sałabun, 2025). Sensitivity analysis can be approached in various ways, primarily depending on the model's methods (Kizielewicz and Sałabun, 2024; Bouraima et al., 2024;

Kannan et al., 2025). In the sensitivity analysis, ten scenarios are formed. This analysis reveals that the most significant changes in the rankings occur for the applications ranked between third and sixth place (Figure 2). This is due to the minimal differences in the results for these applications. Additionally, the sensitivity analysis highlights areas where individual applications can improve to enhance their rankings. For instance, when examining the top two applications, A4 and A8, it is evident that A8 needs to improve C5 - Notification functionality - to surpass A4 in ranking. The sensitivity analysis results indicate that the ranking in favor of A8 only changes when the importance of this criterion is lowered. This demonstrates that A4 has stronger indicators in terms of notification functionality. Similarly, other applications can be analyzed to identify their weaknesses and the specific areas where improvements are needed.

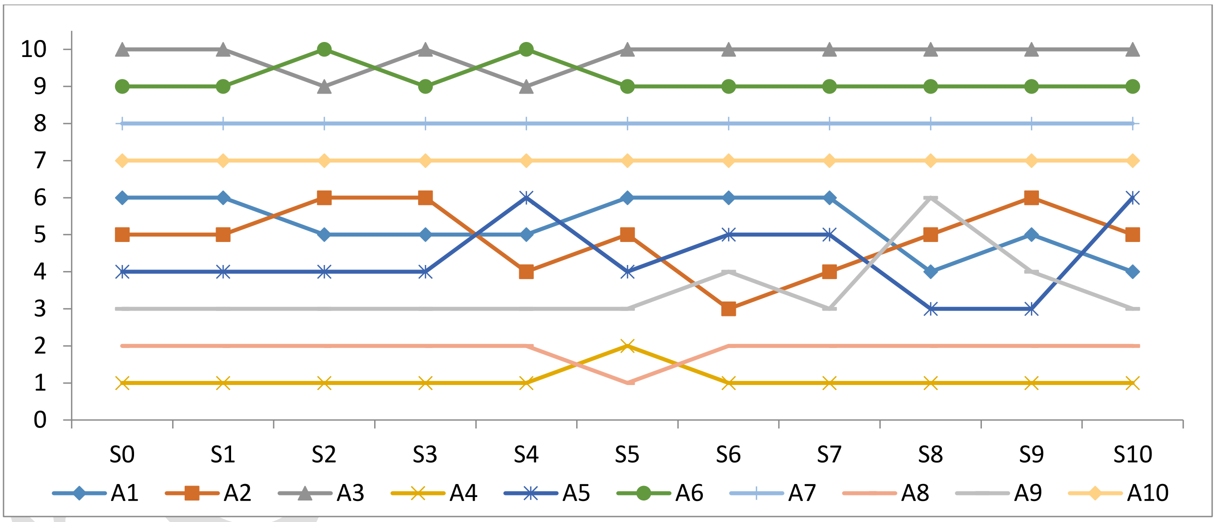

Fig. 2. Sensitivity analysis results

5 | Discusion

With the advancement of smart agricultural production, mobile applications have become increasingly important in managing farming activities. These applications enable farmers to monitor and make informed decisions to improve yields. While such applications were previously more commonly used on large farms, recent technological advancements, particularly in farm-specific IT systems, have reduced the cost of smart agriculture, making it accessible to smaller farms. This study focuses on how certain mobile applications can be used on a small farm like Farmino.

Choosing the most suitable application becomes challenging as the number of applications designed to manage processes on small farms grows. Each application has unique features that distinguish it from others. A decision-making model was developed in this research to address this issue, incorporating relevant criteria and selected mobile applications. The criteria were designed to ensure that the chosen applications were ideal for the unique demands of the Farmino farm. These criteria serve as a guide for what applications should offer to maximize their effectiveness for users. Unlike similar studies that focus on application functionalities (Mendes et al., 2020) or how farmers use these applications (Wang et al., 2024), this study evaluated mobile applications more broadly by using 10 qualitative criteria. These qualitative criteria were chosen to comprehensively assess the applications and provide valuable insights.

Given the qualitative nature of the criteria, the evaluation process utilized linguistic terms. These terms simplified the decision-making process and allowed users to provide imprecise but meaningful assessments (Biswas A. et al., 2024). This approach was particularly appropriate since users had not yet purchased any specific application. Instead, they explored the applications by visiting their websites, reading about their features, and, where possible, downloading free versions to test. Linguistic terms were then applied to evaluate both the importance of the criteria and the applications themselves (Chusi et al., 2024), using a fuzzy approach with appropriate methods. This approach allowed converting linguistic terms to fuzzy numbers (Saraswathi et al., 2024) through defined membership functions (Kumar, 2025).

Two fuzzy methods, SiWeC and LOPCOW, were used to calculate the importance of the criteria. These methods offer subjective and objective ways of determining the importance of criteria. Both methods were employed to reduce subjectivity in the process. However, fuzzy LOPCOW results showed no significant distinction among the criteria. As a result, the weights determined using the fuzzy SiWeC method, based on user ratings, ultimately prevailed. This finding demonstrates that even with efforts to reduce subjectivity, it can still influence outcomes when objective methods fail to prioritize certain criteria or groups of criteria.

The applications were evaluated using fuzzy MABAC. This method stands out compared to others due to several unique steps. First, it applies a different normalization technique. Then, a weight matrix is formed instead of traditional weighting, where the weight values are added to the classic weighting process. Another key difference is that deviations are calculated from the average of all weight matrix values, rather than from the best or worst values, as seen in methods like CRADIS, MARCOS, and ARAS. These specificities resulted in slightly different rankings for two mobile applications, although the top three ranked applications were consistent across all methods. This consistency confirms that the best applications to meet the needs of the Farmino farm were successfully identified.

It is necessary to look at the focus of this discussion from the perspective of the application manufacturer. The results obtained should guide them in which direction to develop their application. What has not been mentioned so far are the platforms for which these applications should be developed. Mobile devices work on different platforms (Bassey et al., 2024), so the application development needs to be adapted to the other operating systems these applications use. This approach will make the manufacturer's applications more accessible to many farmers because they use different mobile devices. Based on this, it can be concluded that these applications will have more potential users (Zubíková et al., 2023).

It should be noted that when applying a decision-making model based on qualitative criteria evaluated subjectively, results can vary, even when using the same criteria and observing the same alternatives. To address this, an effort was made to reduce subjectivity in determining the importance of criteria. However, subjectivity remains essential to this research because the end-users - farmers - will ultimately rely on these applications. They must select the application that best suits their specific needs, enabling them to improve their farming practices through smart agricultural technologies.

6 | Conclusion

Mobile applications can significantly improve the efficiency of small farms. However, for this potential to be fully realized, it is necessary to understand these tools' unique qualities and capabilities. Application evaluation provides farmers with the opportunity to select tools that support their daily management activities, contributing to the long-term sustainability and competitiveness of small farms. This research contributes to developing practical guidelines for selecting and implementing digital tools, helping small farms address challenges more effectively and ultimately improve their productivity and sustainability. Using a practical example from the Farmino farm, this study identified a mobile application that would most effectively enhance the farm's operations.

The results initially highlighted that criterion C6 – Data accuracy had a slight advantage over the other criteria. However, this advantage in weighting was not significant enough to dominate the decision-making process. As a result, all ten criteria contributed equally to determining the most suitable application. Results from fuzzy MABAC and comparative analysis revealed that application A4 produced the best results and was the optimal choice for the Farmino farm. Sensitivity analysis confirmed these findings, showing that application A4 was ranked second only when the importance of criterion C5 - Notification functionality - was reduced.

This research demonstrated how a decision-making model can be constructed and how a combination of MCDM methods could be applied to make a final selection. However, every study that relies on criteria and alternatives has limitations regarding selecting these elements for model formation. Alternative criteria could always be considered, particularly qualitative ones. The same applies to mobile applications, as including every application available on the market or the internet is unreasonable. In this research, the alternatives were primarily constrained by price and accessibility. Therefore, future studies should incorporate additional criteria and explore other applications in the decision-making process, particularly as new applications for small farm management are continually being developed. In addition, other MCDM methods can be used in future research, as comparison with other methods has proven this. Of course, the limitation of this research may be that some applications were omitted, but it is not always possible to take all applications into account. Therefore, a fuzzy approach was applied because there is no complete information in this type of decision-making. Since new applications are constantly emerging, future research must consider them and determine whether any would be better for Farmino.

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Author Contribution

The following statements should be used: "Conceptualization, A.P. and M.N.; Methodology, A.P. and D.B.; Software, A.P.; Validation, A.Š., D.B. and M.N.; formal analysis, A.P.; investigation, M.N.; resources, D.B; data maintenance, A.Š.; writing-creating the initial design, A.Š.; writing-reviewing and editing, A.P. and A.Š.; visualization, A.Š.; monitoring, D.P.; project management, D.P.; funding procurement, M.N. All authors have read and agreed to the published version of the manuscript.

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Data Availability

All data generated or analyzed during this study are included in this published article.

Conflicts of Interest

The authors declare no conflict of interest.

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