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ARTICLE

Selection of Application in Smart Farming Systems

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ABSTRACT

The research presented in this paper was carried out using the example of selecting applications for smart farm management, specifically focusing on the Farmland company. To facilitate this selection process, Multi-Criteria Decision Making (MCDM) methods were employed, including the fuzzy SiWeC (simple weight calculation) method, which was utilized to subjectively assess the significance of the criteria involved, alongside the Entropy method, which objectively evaluated the importance of these criteria. Additionally, the fuzzy CORASO (compromise ranking from alternative solutions) method was applied to rank the alternatives. The assessment of the significance of the criteria, along with the assessment of the applications based on the selected criteria, was conducted by experts. They carried out this assessment by utilizing linguistic values, which required a fuzzy approach. The findings from this approach indicated that, following the application of the SiWeC and Entropy methods, the most critical criterion for assessing applications is their efficiency. Through the application of the fuzzy CORASO method, it was determined that the A1 application most effectively satisfies the established criteria, making it the preferred option for the implementation of the smart farming system. This research has demonstrated that applications are an essential tool for the realization of smart farming, and it has illustrated how applications can be chosen using the MCDM method.

Keywords: Selection of Application; Smart Farming; Fuzzy Approach; Multicriteria Analysis Methods

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1. Introduction

The rise of digitization and the advancement of new technologies have significantly impacted the operations of agricultural production [1]. These transformations have been driven by the integration of innovative technologies into agricultural practices, leading to the development of smart farming. Cutting-edge technologies such as the Internet of Things (IoT), artificial intelligence (AI), the utilization of drones, smart machinery, and big data analytics have been incorporated into this concept [2]. This represents only a fraction of the new technologies being employed in agriculture. Recently, there has been an increasing implementation of AI [3], along with automated systems that enhance productivity within agricultural production through the implementation of smart farming. This concept of agricultural production holds significant importance in attaining efficiency, enhancing productivity, and implementing sustainability, all of which contribute to increased income. This is accomplished through the utilization of precise agricultural production methods that oversee all processes, thereby optimizing resources and minimizing the adverse effects on the environment. Furthermore, as the resources required for agricultural production are diminished, costs are also lowered, leading to greater profitability in this sector. This is accomplished through the implementation of these innovative methods [4]. Such an achievement is not possible without the utilization of smart technology [5].

The defining feature of implementing the smart farming concept is the ability to utilize data acquired through the application of diverse technologies in agriculture. This includes the installation of sensors and the deployment of drones, which serve multiple purposes, ranging from monitoring to treating crops. Sensors facilitate the collection of vital information regarding soil conditions and temperature, while photo sensors can assess the health of crops [6]. These represent just a few of the methods available for gathering information that should serve as the foundation for making decisions about the actions to take to optimize crop quality and increase yields. To analyze this data effectively, specialized applications designed for agricultural production are employed [7]. The utilization of these applications facilitates real-time decision-making by allowing for the implementation of preventive measures. By enhancing these applications with AI, it becomes feasible to make decisions autonomously, without requiring the farmer's involvement. Consequently, contemporary technologies integrated with AI are transforming the fundamental processes of agricultural production.

The utilization of contemporary technologies and the applications that govern them enhances the efficiency of agricultural production. It is essential for agricultural practices to adjust to the climatic conditions that fluctuate daily [8,9]. To implement the concept of smart farming, it is imperative to employ applications that assist in resource management to attain the desired outcomes [10]. The management of resources through applications designed for smart farming leads to a decrease in environmental impact, thereby promoting sustainable agricultural production. Consequently, the implementation of smart farming concepts is crucial for enhancing the competitiveness of agricultural production in rural regions where such production is predominantly practiced.

The concept of smart farming cannot be effectively implemented without utilizing specific applications that assist in agricultural decision-making. These applications evaluate the gathered data and offer real-time decision support [11]. Consequently, choosing the right application is an essential step in the implementation of smart farming. Such applications are crucial and play a vital role in the success of smart farming. Therefore, the process of selecting an application is a significant challenge for farmers. Furthermore, there is a wide array of applications available in the market that can be utilized [12]. It is essential to select the application that will most effectively assist the farmer in adopting smart farming practices. The chosen application should fulfill the farmer's requirements and additionally aid him in making prompt decisions that will enhance his business. The challenge of selecting an application is further exacerbated by the reality that some farmers are only beginning to familiarize themselves with the principles of smart farming and are gradually starting to implement specific technologies. Therefore, it is crucial to streamline and simplify the application selection process to enable an informed decision regarding the choice of a particular application.

This research addresses the challenge of selecting applications within the smart farming system. Consequently, a methodology has been developed to assist in the decision-making process regarding application choices. The decision support is based on the observation that all applications available in the market possess specific functions that are either very similar or identical to those of other applications. Nevertheless, certain applications offer unique features that set them apart from their counterparts. Therefore, it is essential to evaluate the selected applications against specific criteria to gather consistent information about these applications. This will assist in the decision-making process by acquiring a realistic evaluation of the chosen applications. In light of the aforementioned, the objective of this research is to establish a methodological foundation for making decisions regarding the selection of applications for the implementation of smart farming. The selection of applications in this research will be grounded in a case study focusing on the small agriculture enterprise Farmland, which specializes in intensive fruit production.

In order to apply uniformity in decision-making regarding the choice of applications, multi-criteria decision-making methods (MCDM) will be used, as they enable applications to be ranked in accordance with the satisfaction of the set criteria. By applying these methods, an effort will be made first to determine the importance of the selected criteria and then to rank the application in accordance with these criteria. In this way, several criteria are used to evaluate these applications [13]. To implement this decision-making process, scores will be used in the form of linguistic values. This approach aims to make the decision-making process more accessible to typical agricultural producers. By employing scores represented as linguistic values, it necessitates the adoption of a fuzzy approach in decision-making. This methodology relies on the principle that each linguistic value corresponds to a fuzzy number, thereby converting the linguistic values into their respective fuzzy numbers. The distinctive feature of the fuzzy approach is that it does not provide exact values; instead, it emphasizes the nuances of these values, allowing certain fuzzy number values to align with specific linguistic values. Consequently, linguistic values enable decision-making even when the decision maker (DM) lacks complete information, resulting in decisions being made with incomplete data.

In this research, the methodologies SiWeC (simple weight calculation), Entropy, and CORASO (compromise ranking from alternative solutions) were selected to implement the fuzzy approach. The fuzzy SiWeC and Entropy methods will assess the significance of the criteria, whereas the fuzzy CORASO method will establish the ranking of alternatives. Based on this ranking, the appropriate application will be chosen for the implementation of smart farming. In light of the aforementioned points, the contribution of this research is evident in the following:

— Conduct the selection and assessment of criteria, and ascertain the significance of these criteria for choosing the application within the smart farming system.
— Utilize the scores to prioritize and choose the application for implementation in the smart farming system.
— Provide recommendations for the selection of applications in the smart farming system.
— Create a methodology that facilitates the adaptation of the decision-making system for agricultural producers.

The aim of this research is to establish a practical framework for evaluating and selecting applications, utilizing a fuzzy approach that will assist farmers in creating a straightforward decision-making framework for application selection. By employing this method, it will become feasible to identify the application that most effectively meets their requirements.

2. Materials and Methods

The implementation of this research will focus on the case of the Farmland company. This company is relatively new and specializes in agricultural production and the processing of these products. To enhance its operations, it has opted to invest in modern technological devices utilized in the smart farming system. The management of these technologies by the Farmland company will require applications that can gather data from these devices. Consequently, determining which application the company will select to enhance its business is a critical issue. Addressing this challenge will be carried out using the research methodology illustrated in **Figure 1**.

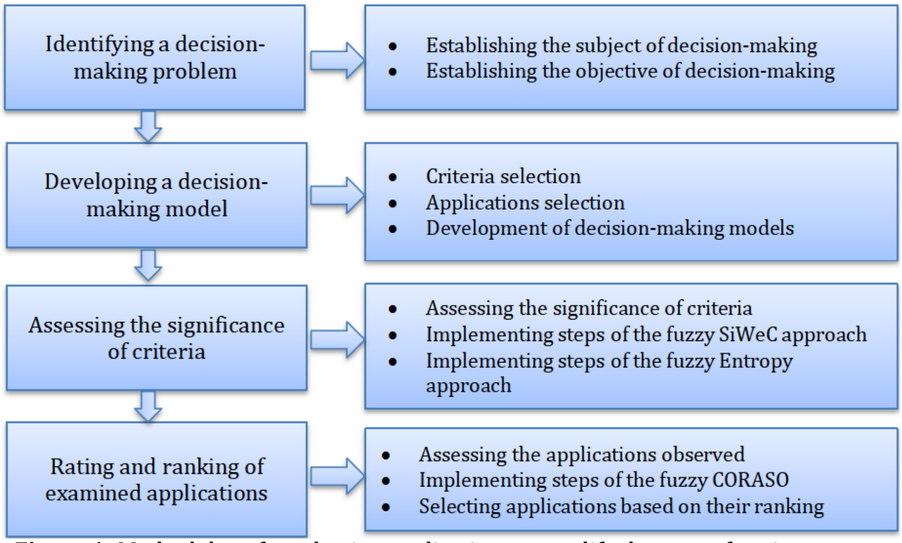

Figure 1. Methodology for selecting applications to modify the smart farming system.

According to the established research methodology (**Figure 1**), it can be concluded that the research will proceed through four distinct steps.

The initial step involves identifying a decision-making problem. In this research, the decision-making problem pertains to selecting the application that will most effectively assist the Farmland company in implementing the smart farming system. This decision-making problem has led to the definition of both the research subject and the objectives of this research.

The second step of this research involves the development of a decision-making model. To implement this phase, it is essential to first identify the DMs for this research. A decision was made to appoint six experts as DMs for this research. Given that the Farmland company is a small organization with a limited number of employees, the selection of DMs was conducted by reaching out to external experts. They were selected because the employees of Farmland have not utilized the applications in their past operations, resulting in a lack of prior knowledge regarding them. These experts are professors at the Faculty of Agriculture in Bijeljina, and this decision was made in collaboration with them. The rationale behind their selection lies in their expertise regarding the applications themselves and the possibilities they present. Furthermore, the manner in which these applications can be utilized was also considered. Initially, these professors were consulted regarding the requirements of the Farmland company, and based on their input, the criteria for this research were established (**Table 1**).

Table 1. Criteria for assessing applications.

Id	Criterion	Description	Reference
C1	Application simplicity	User-friendly application process	Altalak et al. [14]
C2	Application upgrades	Opportunity to upgrade the application	Ilieva & Yankova [15]
C3	Application features	Functions supported by the application	Adamides [16]
C4	Application efficiency	Capability to swiftly process data	Rouyendegh & Savalan [17]
C5	Analysis accuracy	Acquisition of accurate data for informed decision-making	Abualkishik et al. [18]
C6	Customer support	Access to customer support	Puška et al. [19]
C7	Application customization	Customization options available for users	Altalak et al. [14]
C8	Application acceptance	Prevalence of applications in real-world scenarios	Ilieva & Yankova [15]
C9	Additional services	Extra features offered by the application	Puška et al. [19]
C10	Application implementation costs	Overall expenses associated with utilizing the application	Adamides, [16]

Following the selection of the criteria, it is essential to choose the applications that will be examined in this research. In collaboration with DMs, the applications currently available in the market were initially identified, and subsequently, those utilized in these specific areas were chosen. This approach was taken because farmers are already acquainted with these applications and have knowledge of them. Consequently, ten applications were selected for observation in this research. However, since some applications will receive higher rankings while others will be ranked lower, the specific names of the applications will not be disclosed; instead, they will be designated as applications one through ten. Another reason for not utilizing the application's name is that the selection of applications is inherently subjective. Therefore, the application deemed most suitable for the Farmland company may not necessarily be the best fit for another company, and vice versa. This approach helps to preserve the reputation of specific applications. The features of the chosen applications are outlined as follows:

— Application 1 (A1) facilitates effective farm management by overseeing agricultural production, inventory, expenses, and yields.
— Application 2 (A2) allows for the implementation of automated machine control systems to enhance yields and minimize costs.
— Application 3 (A3) enables the tracking of agricultural production and resource inventory by organizing farm activities.
— Application 4 (A4) observes farm operations and provides insights into the farm's condition through diverse analyses.
— Application 5 (A5) encompasses elements for effective farm management by performing various analyses and producing reports.
— Application 6 (A6) facilitates the oversight of agricultural production by organizing related activities.
— Application 7 (A7) employs various analyses of agricultural production through the monitoring of crops and the optimization of farm resources.
— Application 8 (A8) allows for the tracking of finances and the reporting of activities conducted on farms.
— Application 9 (A9) provides the capability to monitor agricultural production and offers a range of analyses and reports.
— Application 10 (A10) allows for real-time monitoring of agricultural production.

Based on the chosen criteria and applications, a decision-making model is established, comprising two components: one for subjectively assessing the weight of the criteria and another for evaluating the applications. In the initial component of the model, the importance of the criteria is solely determined by DMs, whereas in the subsequent component, both criteria and applications are utilized. This latter component is employed to assess the applications in relation to the selected criteria, focusing on how well the applications align with the established criteria.

The third step of this research involves assessing the significance of the criteria. In this research, a blend of subjective and objective approaches will be utilized to ascertain the importance of the criteria. The ultimate weights of the criteria will be established by integrating the weights derived from both methodologies. Consequently, in this phase of the research, two techniques will be employed: fuzzy SiWeC for the subjective assessment of criterion weights and the fuzzy Entropy method for the objective evaluation of criterion weights. Nevertheless, to ascertain these weights, it is essential to employ linguistic assessments of both the criteria and the alternatives. To assist the DMs, the identical scores will be utilized to establish the significance of the criteria and the evaluation of alternatives according to these criteria. These linguistic scores span from very bad to very good, incorporating seven distinct scores that cover these extremes. To evaluate the significance of the criteria, it is imperative to first clarify the selected methods.

The fuzzy SiWeC method is categorized among the methods for the subjective evaluation of criterion importance. This evaluation relies on DMs scores. Utilizing this method, DMs are not required to rank the criteria or to make comparisons between them [20]. It suffices to provide assessments of the significance of each criterion using linguistic values, as a fuzzy approach is employed. Furthermore, this method assesses DMs scores and establishes the significance of their scores, which is a distinctive feature of this approach. The steps of this method are shown below [21]:

Step 1. Assessment of the significance of criteria. The assessment of the significance of the criteria is conducted in a manner whereby the DM assesses the individual significance of each criterion and subsequently assigns scores to these criteria in the form of linguistic values.

Step 2. Conversion of scores into fuzzy numbers. Following the DMs' evaluation of the criteria using linguistic values, it is essential to convert these values into fuzzy numbers. This conversion is achieved through the application of defined membership functions, where each linguistic value is correlated with a specific fuzzy number (**Table 2**).

Table 2. Linguistic value and membership functions.

Linguistic Value	Id	Membership Function
Very bad	VEB	(1, 1, 2)
Bad	BAD	(1, 2, 4)
Medium bad	MEB	(2, 4, 6)
Medium	MED	(3, 5, 7)
Medium good	MEG	(5, 7, 9)
Good	GOO	(7, 9, 10)
Very good	VEG	(9, 10, 10)

Step 3. Data normalization. In this step, all fuzzy numbers are divided by the highest value of the fuzzy numbers.

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

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

Step 4. Calculation of standard deviation ($st.dev_j$). This computation is performed for DM's scores. If the scores exhibit greater uniformity and similarity, the significance of that DM will be reduced, and vice versa.

Step 5. Multiplying normalized scores by standard deviation values. In this phase, the normalized DM's scores are adjusted using the standard deviation value.

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

Step 6. Calculating the total weights for each criterion. In this step, the DM aggregate scores are computed, which serve as the foundation for determining the final weight values of the criteria.

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

Step 7. Determining criteria weights. The ultimate weight values of the criteria are derived by dividing the individual collective weights by the overall collective 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 foundation for determining criteria weights through the fuzzy Entropy method and for ranking criteria via the fuzzy CORASO method relies on the same decision-making matrix. This matrix consists of application evaluations based on specific criteria. Furthermore, the initial three steps in both methods are identical; therefore, these steps will be illustrated solely within the context of the fuzzy Entropy method. This method quantifies the information content and the weight of criteria derived from the entropy value. The groundwork for this method was established by the author Shannon [22] in his research of the mathematical theory of communication. His methodology has been refined in numerous studies to employ this approach as a means of objectively assessing the weight of criteria. The procedure of this method is outlined as follows:

Step 1. Assessment of alternatives using specified criteria. In this step, the DM assesses the applications according to the chosen criteria, thereby determining the extent to which each application satisfies the established criteria.

Step 2. Conversion of scores into fuzzy numbers. In this step, linguistic assessments are converted into fuzzy numbers in accordance with predetermined membership functions (**Table 2**). Subsequently, a collective fuzzy decision-making matrix is established, which reflects the anticipated ratings of all DMs. This approach ensures that each DM holds equal significance in the decision-making process.

Step 3. Normalization of fuzzy numbers. Depending on the nature of the criteria, two forms of normalization are applied. Criteria may manifest as either benefit or cost criteria. For benefit criteria, it is essential that the values be maximized for an alternative to be considered superior, whereas for cost criteria, it is crucial that the values be minimized for an alternative to be deemed better. Cost and benefit serve as accurate representatives of these criteria, thus other criteria are also categorized within this specific type of criteria.

For benefit criteria:

$$n_{ij} = \frac{x_{ij}^l}{\max x_j^u}, \frac{x_{ij}^m}{\max x_j^u}, \frac{x_{ij}^n}{\max x_j^u} \tag{5}$$

For cost criteria:

$$n_{ij} = \frac{\min x_j^l}{x_{ij}^n}, \frac{\min x_j^l}{x_{ij}^m}, \frac{\min x_j^l}{x_{ij}^l} \tag{6}$$

Where: $x_{j\ min}$—the minimum value of a specific criterion, and $x_{j\ max}$—the maximum value of a specific criterion.

Step 4. Determining the Entropy Value (E_i). This value is determined by summing the product of the normalized values and the natural logarithm of the normalized values, which is then divided by the natural logarithm of the number of alternatives observed.

$$E_j = \frac{\sum_{j=1}^{n} n_{ij} \cdot \ln n_{ij}}{\ln n} \tag{7}$$

Step 5. Calculating criteria weights. In this step, the individual difference values and entropy values are divided by the total sum of these values across all criteria.

$$w_{ij} = \frac{1 - E_i}{\sum_{i=1}^{m} (1 - E_i)} \tag{8}$$

Following the implementation of the fuzzy SiWeC and Entropy techniques to ascertain the weight of the criteria, the fuzzy CORASO method will subsequently be employed to establish the ranking of the applications. The fuzzy CORASO method was formulated as a technique that evaluates all alternatives in relation to the maximum and minimum values of the alternative solutions [23]. The steps for this method were outlined by the authors Puška et al. [19].

Given that the initial three steps align with those of the fuzzy Entropy method, the subsequent steps of the fuzzy CORASO method are:

Step 4. Identification of alternative solutions. In this step, alternative solutions are identified, specifically the maximum alternative solution (*max AS*), which represents the highest value among the alternatives for a specific criterion, and the minimum alternative solution (*min AS*), which denotes the lowest value among the alternatives for a specific criterion.

Step 5. Assigning weights to normalized data. In this step, all normalized values are multiplied by their respective weights.

$$\widetilde{v}_{ij} = \widetilde{w}_j \cdot \widetilde{n}_{ij} \tag{9}$$

Step 6. Calculation of aggregate values for weighted alternatives. In this step, aggregate values for all alternatives are computed, encompassing alternative solutions.

$$\widetilde{S}_j = \sum_{i=1}^{n} \widetilde{v}_{ij} \tag{10}$$

Step 7. Calculation of deviations from alternative solutions. The calculation of deviation depends on the specific alternative solutions being considered. For the maximum alternative solution, the deviation is determined by dividing the individual aggregate values of the alternatives by this maximum value, whereas for the minimum alternative solution, the calculation involves dividing this value by the aggregate value of the alternatives.

$$\widetilde{R}_j = \frac{\widetilde{S}_j}{\widetilde{S}_{j\ \max\ AS}} \tag{11}$$

$$\widetilde{R'}_j = \frac{\widetilde{S}_{j\ \min\ AS}}{\widetilde{S}_j} \tag{12}$$

Step 8. Defuzzification. In this step, the conversion of fuzzy values and crisp values is executed.

$$R_{j\ def} = \frac{R_i^l + 4R_i^m + R_i^u}{6} \tag{13}$$

$$R'_{j\ def} = \frac{R'^l_i + 4R'^m_i + R'^u_i}{6} \tag{14}$$

Step 9. Calculation of the CORASO method value.

$$Q_i = \frac{R_j - R'_j}{R_j + R'_j} \tag{15}$$

The best alternative is identified as the one yielding the highest result from the CORASO method, and conversely.

3. Results

In the course of this research, it is essential to first establish the weights of the criteria before proceeding to rank the chosen applications. Consequently, the outcomes derived from the fuzzy SiWeC method will be presented initially. The first step of this method involves evaluating the significance of the criteria through linguistic values (**Table 3**).

The subsequent step involves converting these linguistic values into fuzzy numbers. This conversion is executed through membership functions that are established for the linguistic values (**Table 2**). For instance, the linguistic value 'very good' (VEG) is converted into the fuzzy number (9, 10, 10), and all such values are similarly transformed into fuzzy numbers according to the specified membership function. Once all linguistic values have been converted into fuzzy numbers, the following step is to normalize these values. Initially, the maximum value among all fuzzy numbers is identified, which is 10, and each fuzzy number is divided by this maximum value, resulting in the formation of a normalized fuzzy decision matrix (**Table 4**). Taking DM 1 and criterion C1 as an example, the normalization process is executed as follows:

$$\widetilde{n}_{11} = \frac{7}{10} = 0.7,\ \frac{9}{10} = 0.9,\ \frac{10}{10} = 1.0$$

Table 3. Assessment of the significance of criteria represented by linguistic values.

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
DM 1	GOO	MED	MEG	VEG	VEG	GOO	MED	MEB	MEG	MEG
DM 2	VEG	GOO	MED	VEG	VEG	MEG	GOO	GOO	MEG	GOO
DM 3	VEG	MED	GOO	VEG	GOO	MED	GOO	GOO	GOO	GOO
DM 4	GOO	MED	GOO	GOO	GOO	MEG	MEG	MEG	GOO	MED
DM 5	VEG	MED	MEG	GOO	VEG	MEG	MEG	MEG	GOO	MEG
DM 6	MEG	MEG	MEG	GOO	VEG	MED	GOO	MEB	MED	MED

Table 4. Normalized fuzzy decision matrix.

	C1	C2	C3	C4	C5	...	C10	SD
DM1	0.7, 0.9, 1.0	0.3, 0.5, 0.7	0.5, 0.7, 0.9	0.9, 1.0, 1.0	0.9, 1.0, 1.0	...	0.5, 0.7, 0.9	0.24
DM2	0.9, 1.0, 1.0	0.7, 0.9, 1.0	0.3, 0.5, 0.7	0.9, 1.0, 1.0	0.9, 1.0, 1.0	...	0.7, 0.9, 1.0	0.19
DM3	0.9, 1.0, 1.0	0.3, 0.5, 0.7	0.7, 0.9, 1.0	0.9, 1.0, 1.0	0.7, 0.9, 1.0	...	0.7, 0.9, 1.0	0.21
DM4	0.7, 0.9, 1.0	0.3, 0.5, 0.7	0.7, 0.9, 1.0	0.7, 0.9, 1.0	0.7, 0.9, 1.0	...	0.3, 0.5, 0.7	0.21
DM5	0.9, 1.0, 1.0	0.3, 0.5, 0.7	0.5, 0.7, 0.9	0.7, 0.9, 1.0	0.9, 1.0, 1.0	...	0.5, 0.7, 0.9	0.20
DM6	0.5, 0.7, 0.9	0.5, 0.7, 0.9	0.5, 0.7, 0.9	0.7, 0.9, 1.0	0.9, 1.0, 1.0	...	0.3, 0.5, 0.7	0.24

The subsequent step of the fuzzy SiWeC method involves computing the standard deviation (SD) for the DMs scores (**Table 4**). Once the SD is determined, the normalized DMs scores are multiplied by this value. For instance, in the case of DM1 and criterion C1, the calculation process is executed as follows:

$$\begin{aligned}\widetilde{v}_{11} &= 0.7 \times 0.24 = 0.17,\\ &= 0.9 \times 0.24 = 0.22,\\ &= 1.0 \times 0.24 = 0.24\end{aligned}$$

In this manner, all normalized score values for each DM are multiplied. Following this, the total weights for each criterion are computed. The method for calculating this total using criterion C1 as an example is outlined as follows:

$$\begin{aligned}\widetilde{s}_1 &= (0.17 + 0.17 + 0.19 + 0.14 + 0.18 + 0.12 = 0.97),\\ &= (0.22 + 0.19 + 0.21 + 0.19 + 0.20 + 0.17 = 1.17),\\ &= (0.24 + 0.19 + 0.21 + 0.21 + 0.20 + 0.21 = 1.26)\end{aligned}$$

Following this procedure, all aggregate values of the criteria are computed, culminating in the calculation of the criteria weights. For instance, regarding criterion C1, the process is as follows:

$$\widetilde{w}_1 = \frac{0.97}{11.57} = 0.08,\ \frac{1.17}{9.87} = 0.12,\ \frac{1.26}{7.51} = 0.17$$

Based on DM scores and the steps of the fuzzy SiWeC method, results were derived indicating that criterion C5—Precision of analysis was assigned the highest weight, succeeded by criterion C1—Simplicity of application, and criterion C4—Efficiency of application (**Table 5**). The criterion deemed least significant, which received the lowest weight values according to these findings, is criterion C2—Application upgrade.

Once the weights are established through the fuzzy SiWeC method, they will subsequently be calculated using the fuzzy Entropy method. The execution of the initial three steps of this method mirrors that of the fuzzy CORASO method, as it relies on the evaluations of applications based on chosen criteria. Consequently, the first step involves the evaluation of applications by DMs regarding their compliance with the specified criteria, utilizing linguistic values (**Table 6**).

Table 5. Results of the significance of the criteria based on the steps of the fuzzy SiWeC method.

Criteria	Results of the Significance
C1	(0.08, 0.12, 0.17)
C2	(0.04, 0.08, 0.13)
C3	(0.06, 0.10, 0.15)
C4	(0.09, 0.12, 0.17)
C5	(0.09, 0.13, 0.17)
C6	(0.05, 0.09, 0.15)
C7	(0.06, 0.10, 0.16)
C8	(0.05, 0.08, 0.14)
C9	(0.06, 0.10, 0.16)
C10	(0.05, 0.09, 0.15)

Table 6. Evaluation of applications by experts.

DM 1	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**
A1	VEG	MEG	GOO	GOO	GOO	MEG	MEG	GOO	MEG	MEG
A2	GOO	MEG	MEG	GOO	MEG	MED	MEG	MEG	GOO	GOO
A3	GOO	MEG	MED	MEG	GOO	MEG	MEG	GOO	MEG	MEG
A4	MEG	MED	MEG	MEG	GOO	MEG	GOO	MEG	GOO	MEG
A5	MED	MED	MEB	MED	MEG	MED	MED	MEB	MED	MED
A6	MED	MEG	MEG	GOO	GOO	MED	MEG	MED	MED	MED
A7	MED	MED	MEG	MEG	MEG	MEG	MEG	GOO	MED	MEG
A8	MED	MEG	MEG	MED	MEG	GOO	MEG	MED	MED	MED
A9	GOO	GOO	GOO	MEG	GOO	VEG	MEG	MED	MEG	MEG
A10	GOO	MED	MED	BED	MEG	MEG	MEG	GOO	GOO	MEG
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
DM 6	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**
A1	VEG	VEG	VEG	GOO	GOO	VEG	VEG	GOO	GOO	GOO
A2	VEG	VEG	MEG	GOO	MEG	GOO	MEG	MEG	GOO	VEG
A3	VEG	MEG	GOO	MEG	GOO	GOO	MEG	GOO	MEG	GOO
A4	GOO	MEG	MEG	GOO	GOO	GOO	GOO	MEG	GOO	MEG
A5	GOO	MED	MED	GOO	MEG	MED	MEG	GOO	MED	GOO
A6	GOO	MEG	MEG	MEG	GOO	MEG	MEG	MEG	MED	MEG
A7	VEG	MED	MED	MEG	MEG	MEG	MEG	GOO	MED	MEG
A8	VEG	MEG	GOO	GOO	MEG	GOO	MEG	MEG	MEG	VEG
A9	GOO	GOO	GOO	MEG	MEG	VEG	GOO	MED	MEG	MEG
A10	MEG	VEG	MED	MED	MEG	GOO	MEG	MEB	GOO	GOO

Subsequently, the conversion of linguistic values into fuzzy numbers occurs in a manner analogous to that employed with fuzzy SiWeC, utilizing the same linguistic values and membership function. The following step involves the creation of a collective decision-making matrix. This decision-making matrix is established by calculating the average value of fuzzy numbers across all six DMs. By adhering to this principle, equal significance is assigned to all DMs within the decision-making process, ensuring that their assessments have a uniform impact on the ultimate ranking of applications. Following this, the aggregated decision-making matrix undergoes normalization. Given that the linguistic values are established within a range from very poor to very good, all DM scores are represented as benefit criteria, thus necessitating the application of benefit normalization (**Table 7**). For instance, in the case of application A1 and criterion C1, the normalization process is executed as follows:

$$\widetilde{n}_{11} = \frac{8.33}{10.00} = 0.83,\ \frac{9.67}{10.00} = 0.97,\ \frac{10.00}{10.00} = 1.00$$

Table 7. Normalized cumulative decision-making matrix.

	C1	C2	C3	C4	...	C10
A1	0.83, 0.97, 1.00	0.70, 0.88, 0.98	0.80, 0.95, 1.00	0.70, 0.90, 1.00	...	0.37, 0.42, 0.52
A2	0.77, 0.93, 1.00	0.57, 0.75, 0.92	0.50, 0.70, 0.90	0.70, 0.90, 1.00	...	0.37, 0.39, 0.46
A3	0.87, 0.98, 1.00	0.50, 0.70, 0.90	0.63, 0.83, 0.95	0.50, 0.70, 0.90	...	0.37, 0.42, 0.52
A4	0.43, 0.63, 0.82	0.33, 0.53, 0.73	0.50, 0.70, 0.90	0.63, 0.83, 0.97	...	0.48, 0.65, 1.00
A5	0.43, 0.63, 0.80	0.30, 0.50, 0.70	0.28, 0.48, 0.68	0.50, 0.70, 0.85	...	0.48, 0.61, 0.92
A6	0.37, 0.57, 0.75	0.50, 0.70, 0.90	0.50, 0.70, 0.90	0.63, 0.83, 0.97	...	0.48, 0.65, 1.00
A7	0.60, 0.75, 0.85	0.30, 0.50, 0.70	0.33, 0.53, 0.73	0.50, 0.70, 0.90	...	0.41, 0.52, 0.73
A8	0.63, 0.80, 0.90	0.50, 0.70, 0.90	0.57, 0.77, 0.93	0.57, 0.77, 0.90	...	0.41, 0.47, 0.61
A9	0.70, 0.90, 1.00	0.70, 0.90, 1.00	0.70, 0.90, 1.00	0.50, 0.70, 0.90	...	0.41, 0.52, 0.73
A10	0.67, 0.85, 0.97	0.77, 0.90, 0.95	0.30, 0.50, 0.70	0.27, 0.45, 0.65	...	0.37, 0.42, 0.55

After the normalized cumulative decision matrix has been established, the specific steps of fuzzy Entropy and CORASO are executed. The following step in the fuzzy entropy method involves determining the entropy value. Taking criterion C1 as an example, this value is computed in the manner outlined below:

$$\begin{aligned} E_1 &= \frac{0.83 \cdot \ln(0.83) + 0.77 \cdot \ln(0.77) + 0.87 \cdot \ln(0.87) + \ldots + 0.67 \cdot \ln(0.67)}{\ln(10)} = -1.17, \\ &= \frac{0.97 \cdot \ln(0.97) + 0.93 \cdot \ln(0.93) + 0.98 \cdot \ln(0.98) + \ldots + 0.85 \cdot \ln(0.85)}{\ln(10)} = -0.71, \\ &= \frac{1.00 \cdot \ln(1.00) + 1.00 \cdot \ln(1.00) + 1.00 \cdot \ln(1.00) + \ldots + 0.97 \cdot \ln(0.97)}{\ln(10)} = -0.36 \end{aligned}$$

Utilizing the computed entropy value, the ultimate criterion weight is derived through the fuzzy entropy method (**Table 8**). In the case of criterion C1, the calculation of the criterion weight is carried out as follows:

$$\widetilde{n}_{11} = \frac{1-(-1.17)}{23.84} = 0.06,\ \frac{1-(-0.71)}{20.17} = 0.10,\ \frac{1-(-0.36)}{15.24} = 0.15$$

Table 8. Weights of criteria utilizing the fuzzy Entropy method and the final weights of the criteria.

Criteria	C1	C2	C3	C4	C5
E_i	−1.17, −0.71, −0.36	−1.37, −1.00, −0.50	−1.37, −0.99, −0.49	−1.36, −0.89, −0.37	−1.33, −0.81, −0.24
w_{ij}	0.06, 0.08, 0.14	0.06, 0.10, 0.16	0.06, 0.10, 0.16	0.06, 0.09, 0,16	0.05, 0.09, 0.15
Final w_{ij}	0.07, 0.10, 0.15	0.05, 0.09, 0.14	0.06, 0.10, 0.15	0.07, 0.11, 0.16	0.07, 0.11, 0.16
Criteria	**C6**	**C7**	**C8**	**C9**	**C10**
E_i	−1.30, −0.88, −0.40	−1.57, −1.42, −0.88	−1.40, −1.01, −0.52	−1.39, −1.01, −0,50	−1.58, −1.46, −0.96
w_{ij}	0.06, 0.09, 0.15	0.08, 0.12, 0.17	0.06, 0.10, 0.16	0.06, 0.10, 0.16	0.08, 0.12, 0.17
Final w_{ij}	0.06, 0.09, 0.15	0.07, 0.11, 0.16	0.06, 0.09, 0.15	0.06, 0.10, 0.16	0.07, 0.11, 0.16

The findings from the implementation of the fuzzy Entropy method indicate that criterion C10—Costs of application was deemed the most significant, succeeded by criterion C7—Adaptability of the application, whereas criterion C1—Simplicity of the application was regarded as the least important (**Table 8**).

Once the weights have been established through the fuzzy Entropy method, the ultimate weights of the criteria are computed by averaging the weights derived from the fuzzy SiWeC and Entropy methods. This computation is exemplified using C1 as follows:

$$\begin{aligned} \widetilde{n}_{11} &= \frac{0.06+0.08}{2} = 0.07, \\ &= \frac{0.08+0.12}{2} = 0.10, \\ &= \frac{0.14+0.17}{2} = 0.15 \end{aligned}$$

The results of the final weights (**Table 8**) indicate that criterion C4—Efficiency of the application was assigned the highest weight. Thus, by employing both subjective and objective approaches, the final weights of the criteria were determined. The application of these two methods aimed to minimize subjectivity in the decision-making process regarding the selection of an application to meet the requirements of the Farmland company.

Having computed the weights of the criteria, the final rankings of the applications are subsequently determined through the fuzzy CORASO method. Following the initial three identical steps utilized in the fuzzy Entropy method, alternative solutions are identified. The identification of these solutions is executed in a manner that seeks to ascertain the maximum and minimum values of normalized data for specific criteria. For instance, with respect to criterion C1, the maximum solution alternative is represented as $max\ AS = 0.87,\ 0.98,\ 1.00$, whereas the minimum solution alternative is denoted as $min\ AS = 0.37,\ 0.57,\ 0.75$.

Subsequently, the normalized decision-making matrix is weighted by incorporating alternative solutions. Taking criterion C1 and application A1 as an example, this process is carried out as follows:

$$\begin{aligned}\widetilde{v}_{11} &= 0.83 \cdot 0.07 = 0.06,\\ &= 0.97 \cdot 0.10 = 0.10,\\ &= 1.00 \cdot 0.15 = 0.15\end{aligned}$$

Subsequently, aggregated values of the weighted data are generated for each alternative. This process involves summing the relevant fuzzy numbers associated with each alternative, including alternative solutions. Following this, deviations from the alternative solutions are computed (**Table 9**). For instance, in the case of application A1, this is executed as follows:

$$\widetilde{R}_1 = \frac{0.41}{1.55} = 0.27,\ \frac{0.79}{0.87} = 0.91,\ \frac{1.37}{0.45} = 3.02,$$
$$\widetilde{R'}_1 = \frac{0.22}{1.37} = 0.16,\ \frac{0.50}{0.79} = 0.63,\ \frac{1.04}{0.41} = 2.51$$

Table 9. Results of application ranking using the fuzzy CORASO method.

	$\widetilde{S}_j$	$\widetilde{R}_j$	$\widetilde{R'}_j$	$R_{j\ def}$	$R'_{j\ def}$	Q_i	**Rank**
A1	0.41, 0.79, 1.37	0.27, 0.91, 3.02	0.16, 0.63, 2.51	1.153	0.869	0.141	1
A2	0.35, 0.71, 1.34	0.23, 0.82, 2.95	0.16, 0.70, 2.97	1.074	0.992	0.039	4
A3	0.37, 0.74, 1.38	0.24, 0.85, 3.04	0.16, 0.67, 2.80	1.117	0.941	0.085	2
A4	0.34, 0.70, 1.37	0.22, 0.81, 3.01	0.16, 0.71, 3.08	1.078	1.014	0.030	5
A5	0.27, 0.60, 1.25	0.17, 0.69, 2.76	0.18, 0.84, 3.93	0.948	1.241	−0.134	10
A6	0.31, 0.66, 1.34	0.20, 0.76, 2.95	0.16, 0.75, 3.39	1.034	1.094	−0.028	8
A7	0.30, 0.64, 1.28	0.19, 0.73, 2.81	0.17, 0.79, 3.51	0.988	1.138	−0.070	9
A8	0.33, 0.68, 1.32	0.21, 0.78, 2.90	0.17, 0.74, 3.19	1.040	1.051	−0.005	6
A9	0.36, 0.73, 1.36	0.23, 0.84, 3.00	0.16, 0.69, 2.90	1.095	0.969	0.061	3
A10	0.33, 0.67, 1.29	0.21, 0.78, 2.84	0.17, 0.74, 3.20	1.026	1.056	−0.015	7
MAX AS	0.45, 0.87, 1.55						
MIN AS	0.22, 0.50, 1.04						

Next, defuzzification occurs, wherein fuzzy numbers are converted into crisp numbers. In the case of application A1, this is determined as follows:

$$R_{1def} = \frac{0.27 + 4 \cdot 0.91 + 3.02}{6} = 1.153,$$
$$R'_{1def} = \frac{0.16 + 4 \cdot 0.63 + 2.51}{6} = 0.869$$

The final step of the fuzzy CORASO method entails calculating the value of this method. In the context of alternative A1, the ultimate value is computed as follows:

$$Q_1 = \frac{1.153 - 0.869}{1.153 + 0.869} = 0.141$$

The results derived from the implementation of the fuzzy CORASO method and the scores of DMs indicate that application A1 yields the most favorable results, succeeded by application A3, whereas the least favorable alternative is A10 (**Table 9**). Consequently, the first selection for the Farmland company is application A1, as the DMs believe that this application would most effectively assist the company in reaching its objectives.

4. Discussion

The advancement of technology and the digitalization of business within the agricultural sector have necessitated the adoption of applications designed to manage processes and facilitate smart farming. These applications have become essential tools in agriculture, as evidenced by the research conducted by Altalak et al.[14], who highlights the significance of applications for utilizing data gathered in the field through smart farming tools. Beyond their capability to process field data, these applications can also leverage online data, including meteorological information, to perform specific actions that contribute to crop development and enhance farm operations. In the research conducted by Adamides[16], it was demonstrated that through the use of precision agricultural production applications, measures can be implemented to mitigate the adverse effects of climate change on agriculture. These applications are designed to deliver precise and accurate information, enabling farmers to make timely decisions that will first safeguard their crops from climate change and subsequently enhance the productivity of their agricultural output. Numerous authors in earlier studies have emphasized the significance of applications within the smart farming system[15,17,18,24], highlighting the necessity to explore the effects of these applications in this context. Consequently, this research selected an application that would optimally assist the company Farmland in adopting the smart farming system for agricultural production.

To conduct this research, a decision-making model was developed based on the subjective evaluations of DMs. This model facilitated the selection of ten criteria along with ten applications that were analyzed using these criteria. The criteria were chosen in alignment with the objectives of the Farmland company concerning the implementation of the smart farming system. Given that Farmland lacked the necessary capacity and expertise regarding applications in the smart farming system, it opted to engage external specialists to address this issue. They chose to enlist professors from the Faculty of Agriculture in Bijeljina, as these professors possess knowledge of the applications related to the smart farming system through their scientific research endeavors. Furthermore, they are well-acquainted with the applications available in the market that are utilized in these domains to meet the requirements of this system. With the help of these DMs, criteria were selected for the needs of this research, where the focus was on qualitative criteria, where the basis was the functionality and application of these applications. Due to the specificity of the criteria itself, it was chosen to use linguistic values for the evaluation of these criteria[25]. The specificity of these values is that it is not necessary to have complete information about a certain problem, but it is possible to carry out the decision-making process using incomplete information[26]. These linguistic values were also used in the assessment of applications. In order to use these values in determining the importance of criteria and evaluating applications, a fuzzy approach was used[27]. This approach enables the nuance of linguistic values so that this value includes different values of fuzzy numbers[28].

In assessing the significance of the criteria, a combination of subjective and objective methodologies was employed. Subjective methods were utilized to ascertain the importance of the criteria based solely on the ratings provided by DMs[29]. Consequently, two distinct approaches were implemented to mitigate the subjective bias of DMs during the decision-making process. To effectively apply this methodology in evaluating the importance of the criteria, two fuzzy techniques, namely SiWeC and Entropy, were used. The fuzzy SiWeC method was specifically employed to subjectively assess the importance of the criteria by utilizing the scores from DMs. This method was chosen due to its ease of application, as it also facilitates the assessment of the significance and evaluation of individual DMs. The application of this method yielded results indicating that, according to the opinions of DMs, the criterion of analysis precision is deemed the most significant. The reason for this is that the implementation of modern technologies in smart farming yields substantial amounts of data, necessitating precise analysis to derive the appropriate data for making decisions regarding which measures to implement. The fuzzy Entropy method is classified among the techniques used to objectively assess the significance of criteria. This category of methods fundamentally relies on evaluations of alternatives based on specific criteria to compute weights[30]. The weight calculations using these methods are performed based on the variability of evaluations of alternatives concerning certain criteria[31]. Consequently, the Entropy method assesses the significance of criteria by utilizing the entropy value[32]. The findings from this method indicate that the criterion related to application costs yielded the most favorable results. Nevertheless, when the average weights for the outcomes of these two methods were computed, the criterion for application efficiency demonstrated the most advantageous results. This is attributed to the fact that in both methods, this criterion was closely aligned with the top-performing criteria, and the compromise of these weights identified it as the most critical criterion for ranking alternatives.

The distinctive feature of the fuzzy Entropy and CORASO methods is that they share the same initial three steps, leading to the development of a hybrid entropy CORASO method for application selection. The CORASO method was selected due to its favorable performance when compared to other MCDM methods, as it offers a reliable ranking of alternatives [13]. This method was employed to rank the ten applications that the DMs considered the most suitable for smart farming at Farmland. Naturally, there exists a significantly larger array of applications available in the market that can cater to the requirements of smart farming. It is impractical to encompass all applications within a specific study, as some are tailored for different agricultural practices, such as animal husbandry, for instance. Consequently, an assessment of these ten applications was conducted, which were appraised by the DMs. The findings from the implementation of the fuzzy CORASO method indicated that the A1 application emerged as the most effective solution for the Farmland company, facilitating the efficient integration of the smart farming system into agricultural production. The rationale behind this application's top rating lies in its capability to enhance the efficiency and productivity of agricultural production. It achieves this by enabling the monitoring of resource consumption, overseeing stock levels, and facilitating the collection and analysis of diverse data, which in turn supports timely decision-making. Consequently, it is essential to select an application that offers a comprehensive array of options for managing agricultural production.

5. Conclusions

In this research, the application was chosen for implementing the smart farming system in agricultural production. This system was developed alongside advancements in technology and the digitization of business, aimed at modernizing agricultural practices. The choice of this application was based on the example of the Farmland company. This company is characterized as a small entity with a limited workforce, dedicated to enhancing agricultural production. Consequently, external experts were engaged for this selection process. A total of 10 applications and an equal number of criteria were evaluated. The criteria selection was based on the technical, functional, and economic dimensions of these applications. In the process of selecting applications, the MCDM approach was employed for decision-making. This approach was selected due to the presence of multiple criteria that were utilized to evaluate several applications. Consequently, a compromise decision is reached that aims to satisfy these criteria. MCDM methods served as instruments in the decision-making process; while they do not enhance the efficiency of agricultural production directly, they do improve the efficiency of decision-making, facilitating timely decisions. Thus, these methods do not have a direct impact on the efficiency of the smart farming system, but rather an indirect effect through the decision-making process.

A combination of three fuzzy methods was employed in the selection of applications. The Fuzzy Entropy and SiWeC methods were utilized to assess the significance of criteria in the application selection process. By implementing these two methods, an attempt was made to gather information regarding the importance of the criteria in both subjective and objective manners. The integration of these methods aims to reduce subjectivity in decision-making. The outcomes of this combination revealed that the most critical criterion is the efficiency of applications. Through additional analysis, the ranking of these applications was established based on the evaluations of decision-makers (DMs). This ranking was conducted using the fuzzy CORASO method. The rationale for employing the ranking of alternatives is to ascertain how effectively each application fulfills the established criteria in this decision-making process. The findings from the fuzzy CORASO method indicated that the A1 application received the highest ratings and is expected to assist the Farmland company in utilizing the smart farming system to enhance agricultural production.

The benefits of this decision-making approach regarding the selection of applications lie in its simplicity and flexibility, allowing for effective choices not only in agriculture but also in any decision-making scenario that requires the ranking of alternatives. Nevertheless, a limitation of this research is its inability to encompass all potential criteria and applications relevant to this decision-making process. Consequently, it was essential to identify the criteria that align most closely with the objectives of the Farmland company, as well as the applications that could facilitate the implementation of the smart farming system. This research, therefore, provided guidelines on how to select applications and the criteria to employ in this selection process. The importance of this lies in the fact that applications serve as vital tools for integrating modern technologies into agriculture. It is imperative for every farmer to adapt to these technologies and strive to utilize them to enhance their business.

The research conducted provided both theoretical and practical implications for the advancement of the smart farming system. Primarily, a decision-making model was developed that offered guidance on the criteria to consider when selecting applications. These criteria are tailored to the requirements of the Farmland company, necessitating further adaptation to meet the needs of other companies or farmers making application choices. Furthermore, this research has contributed to the evolution of smart farming theory, as it elucidated the concept and established that applications are essential tools for this agricultural production system. The practical implications derived from this research should be reflected in the actual application of the application selection process. The selection of applications is customized to the specific needs of a company, thereby enhancing its business operations. Additionally, by utilizing the MCDM method, practical guidelines are provided for selecting applications through a real-world example. Consequently, it is imperative to further develop the guidelines established by this research in future studies to enhance the operations of agricultural companies within the agricultural production framework.

Author Contributions

Conceptualization, J.B. and M.N.; methodology, A.P.; software, A.P.; validation, J.B., and M.N.; formal analysis, A.P.; investigation, M.N.; resources, J.B.; data curation, J.B.; writing—original draft preparation, J.B.; writing—review and editing, A.P.; visualization, A.P.; supervision, J.B.; project administration, A.P.; funding acquisition, J.B. All authors have read and agreed to the published version of the manuscript.

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

Conflicts of Interest

The authors declare no conflicts of interest.

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