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Agritech Decision Support System Using the SMART Method for Determining Optimal Oil Palm Seedling Pollination at PT. Bakrie Sawit Unggul

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Abstract: The selection of superior oil palm seed pollination methods at PT. Bakrie Sawit Unggul (PT. Bakrie Sumatera Plantations Tbk) has conventionally relied on field experience and intuition, leading to subjective, inconsistent, and less measurable operational decisions. To address this limitation, this study develops a web-based smart agritech Decision Support System using the Simple Multi-Attribute Rating Technique (SMART) method to determine the optimal pollination strategy. The system evaluates ten pollination alternatives across five operational criteria: the number of flowers pollinated, pollination success rate, processing time, labor requirement, and pollination failure rate. Operational data were gathered through direct field observations, structured interviews, production documentation, and literature review. To facilitate multi-criteria evaluation, raw operational indicators were standardized into a 1–5 preference scale and treated as benefit criteria during linear utility calculations. The software was developed using PHP and MySQL, with functional validation conducted via Black Box Testing to ensure computational accuracy and system reliability. The calculation results demonstrate that Intensive Pollination combined with standard operating procedures (Intensive Pollination + SOP, A10) achieved the highest utility score of 0.8500, outperforming Scheduled Pollination + SOP (0.7794) and Standard SOP Pollination (0.7419). Although Alternative A10 requires greater labor allocation, this requirement is heavily compensated by superior biological success and minimized defect rates across production cycles. These findings confirm that the system provides an objective, transparent, and reproducible decision-making framework, standardizing pollination practices, mitigating production risks, and optimizing resource allocation in Seed Garden management.

Keywords: Decision Support System; Oil Palm; Pollination; SMART; Superior Seeds.

1. Introduction

The rapid development of digital technologies has driven significant transformation across the agricultural and plantation sectors. Traditional cultivation practices that rely predominantly on human intuition and manual field experience are steadily shifting toward smart agriculture, where information technology, Internet of Things (IoT) sensors, and Decision Support Systems (DSS) facilitate objective, data-driven decision-making (Mansoor *et al.*, 2025; Nair, 2025; Wolo *et al.*, 2023). In modern plantation management, DSS serves as a vital tool to process multi-variable data and generate reliable operational recommendations (Chandana *et al.*, 2024; Kabo *et al.*, 2025). Within plant breeding, the application of decision support models is particularly critical during pollination, which directly governs seedling viability, genetic purity, and overall oil palm productivity (Syarif Hidayat & Eliyani, 2023). Inefficient or subjective pollination management increases the risk of seed defects, elevates production costs, and compromises the continuous supply of high-grade commercial planting materials. At PT. Bakrie Sawit Unggul, situated in Sidomukti, Kisaran Barat District, Asahan Regency, North Sumatra, pollination management in the Seed Garden is still executed through conventional manual procedures. Consequently, operational evaluations depend heavily on field supervisor observations, introducing subjectivity and inconsistency into daily decisions. This manual approach presents substantial challenges in monitoring pollination performance across cycles and handling interdependent operational variables, such as flower availability, technician capacity, working hours, and success rates. The operational variations observed across plantation blocks are detailed in Table 1.

Table 1. Pollination Performance Across Plantation Blocks at PT. Bakrie Sawit Unggul

No.	Block	Number of Female Flowers	Number of Pollinated Flowers	Successful	Failed	Time (Hours)	Workers
1	Dura 1	35	30	25	5	3	2
2	Dura 2	40	36	30	6	4	2
3	Dura 3	38	32	27	5	3	2
4	Dura 4	42	37	31	6	4	3
5	Dura 5	45	40	34	6	4	3

Note. Data collected from field documentation at PT. Bakrie Sawit Unggul (2025).

The field data in Table 1 demonstrate notable variations in pollination outcomes across different blocks, underscoring that operational success depends on multiple interrelated factors, including flower volume, labor allocation, execution duration, and failure thresholds. Resolving these operational trade-offs requires a structured multi-criteria decision-making framework (Hamidani & Apriadi, 2024). To address this need, the Simple Multi-Attribute Rating Technique (SMART) provides an effective approach due to its transparent linear weighting mechanism, computational simplicity, and ease of interpretation for plantation supervisors (Taherdoost & Mohebi, 2024). While methods such as the Analytic Hierarchy Process (AHP) require extensive pairwise comparison matrices and consistency verifications, and TOPSIS involves complex Euclidean distance calculations to ideal solutions, SMART enables straightforward weight assignment and direct linear utility conversion (Nasyuha *et al.*, 2025). These characteristics make SMART particularly suitable for integration into a web-based decision platform that can be operated efficiently in day-to-day plantation workflows. This study develops a web-based Smart Agritech Decision Support System utilizing the SMART method to determine the optimal pollination strategy for superior oil palm seedlings at PT. Bakrie Sawit Unggul. The evaluation models ten practical pollination alternatives, ranging from conventional manual practices to scheduled and intensive pollination protocols with Standard Operating Procedure (SOP) integration. Assessment is conducted across five essential operational criteria: number of flowers pollinated, pollination success rate, processing time, labor requirement, and pollination failure rate. By converting multi-dimensional field variables into standardized preference utilities, the proposed system aims to deliver objective, transparent, and reproducible recommendations to enhance seed quality and operational efficiency in Seed Garden management.

2. Related Work

2.1 Decision Support System (DSS)

A Decision Support System (DSS) is an interactive information system designed to assist decision-makers in resolving semi-structured and unstructured problems by integrating operational data, analytical models, and user-friendly interfaces (Jana *et al.*, 2022). In organizational and operational settings, a DSS does not replace human judgment; rather, it extends managerial capabilities by systematically generating objective evaluations, scenario analyses, and prioritized recommendations (Sudipa *et al.*, 2023). In agricultural and plantation contexts, DSS applications have expanded from routine inventory and financial monitoring to complex agronomic interventions, including fertilizer optimization, land suitability assessment, and crop breeding management (Mansoor *et al.*, 2025; Wolo *et al.*, 2023).

2.2 SMART Method

The Simple Multi-Attribute Rating Technique (SMART), originally developed by Ward Edwards, is a multi-criteria decision-making (MCDM) method grounded in multi-attribute utility theory. The method evaluates alternative solutions by assigning relative weights to predetermined criteria and converting raw performance values into standardized linear utility scales bounded between 0 and 1 (Taherdoost & Mohebi, 2024). The final preference value for each alternative is determined through an additive weighting model, in which the normalized rating of each criterion is multiplied by its corresponding weight. SMART is widely favored in operational decision environments because it provides computational transparency, requires minimal mathematical complexity compared to pairwise comparisons, and reliably produces stable alternative rankings (Nasyuha *et al.*, 2025).

2.3 Comparison of Related Studies

Recent studies demonstrate that Decision Support Systems significantly improve agricultural decision-making by combining multi-criteria analysis with digital processing frameworks (Munir & Rahardiyanto, 2023). Previous implementations of the SMART method have demonstrated strong utility across diverse operational problems, such as superior seed selection, fertilizer recommendation, and agricultural marketing strategies (Kabo *et al.*, 2025; Kamis *et al.*, 2022; Syarif Hidayat & Eliyani, 2023). However, empirical applications evaluating artificial pollination strategies in commercial oil palm seed production remain scarce. Table 2 summarizes recent representative studies in agricultural DSS and multi-criteria decision-making to delineate the context and contribution of this work.

Table 2. Comparison of Previous Studies on Decision Support Systems and the SMART Method

Author	Method	Application	Research Contribution	Research Gap
Munir & Rahardiyanto (2023)	DSS	Agricultural management	Demonstrated the use of DSS to improve agricultural decision-making	Did not apply the SMART method for evaluating oil palm pollination lternatives
Chandana *et al.* (2024)	MCDM	Agricultural evaluation	Proposed multi-criteria evaluation for agricultural decision support	Focused on general crop monitoring rather than pollination strategy selection
Taherdoost & Mohebi (2024)	SMART	Multi-criteria decision making	Explained the advantages of SMART in terms of simplicity, transparency, and computational efficiency	Did not develop a web-based operational system for plantation management
Nasyuha *et al.* (2025)	SMART, SAW, TOPSIS	Comparative DSS	Demonstrated that SMART yields consistent rankings with lower computational complexity than SAW and TOPSIS	Did not address operational pollination problems in superior oil palm seed production
This study	SMART	Oil palm Seed Garden	Develops a web-based Decision Support System for selecting pollination methods using operational criteria	Integrates practical field constraints into a digital platform for Seed Garden operations at PT. Bakrie Sawit Unggul

Note. Synthesis of related studies comparing decision support approaches and empirical domains.

As outlined in Table 2, while multi-criteria decision models have been widely investigated, existing literature predominantly focuses on high-level crop suitability, comparative algorithmic performance, or promotion strategies without addressing the operational complexities of oil palm Seed Garden operations. Prior agricultural DSS models often overlook shop-floor pollination constraints, such as flower availability, technician capacity, execution duration, and failure thresholds. This study bridges that gap by implementing the SMART method within a dedicated web-based decision support system tailored to PT. Bakrie Sawit Unggul. By transforming multi-dimensional operational metrics into standardized linear utilities, the proposed system provides a transparent, objective, and reproducible framework to standardize pollination practices and enhance superior seed productivity.

3. Methodology

3.1 Research Framework

This section outlines the research methodology and operational framework designed to select the optimal pollination strategy for superior oil palm seedlings at PT. Bakrie Sawit Unggul. The staged methodology encompasses problem identification, system modeling, software development, black-box testing, and operational implementation using field data, as illustrated in Figure 1.

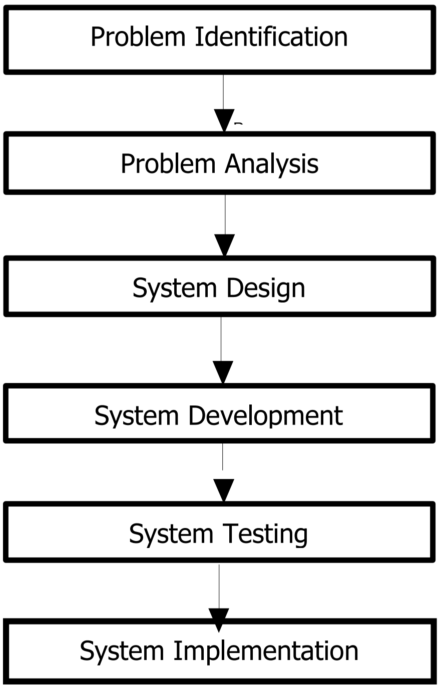

Figure 1. Research Framework

The study began with problem analysis concerning the existing pollination management at PT. Bakrie Sawit Unggul, where decisions were primarily made based on conventional field observations without standardized multi-criteria metrics. To provide a systematic solution, the decision architecture was designed using Unified Modeling Language (UML) diagrams (Ramdany *et al.*, 2023), operational flowcharts, and dedicated database schemas. The web application was implemented using PHP and MySQL, and the functionality of all computational routines was verified through Black Box Testing prior to deployment (Wijaya *et al.*, 2024). Empirical data were gathered through direct field observations, structured interviews with plantation supervisors, internal production documentation, and literature review. The evaluation models ten practical pollination alternatives evaluated across five decision criteria: number of flowers pollinated, pollination success rate, processing time, labor requirement, and pollination failure rate. Although operational processing time, labor requirements, and failure rates naturally represent cost dimensions, these metrics were mapped onto a standardized 1–5 preference scale where higher ratings consistently denote superior performance. Consequently, all criteria were treated as benefit criteria during linear utility calculations, eliminating scale distortions while preserving empirical validity (Taherdoost & Mohebi, 2024).

3.2 Mathematical Formulation of the SMART Method

The Simple Multi-Attribute Rating Technique (SMART) operates on an additive multi-attribute utility model. The computation begins by normalizing the raw criterion weights assigned by plantation experts so that their sum equals 1, formulated as follows:

$$w_j = \frac{W_j}{\sum_{j=1}^{m} W_j} \quad (1)$$

Where wj is the normalized weight of the $j - th$ criterion, Wj is the initial weight assigned to the $j - th$ criterion, and m is the total number of evaluation criteria. After establishing normalized weights, each alternative's performance metric is converted into a utility value . For benefit criteria, where higher values represent greater preference, the utility calculation is expressed as:

$$R_{ij} = \frac{X_{ij} - X_{min}}{X_{max} - X_{min}} \quad (2)$$

Where Rij is the normalized utility value of alternative i on criterion j, Xij is the actual performance score of alternative i on criterion j, while $Xmax$ and $Xmin$ represent the maximum and minimum values observed for criterion j, respectively. For standard multi-criteria models containing cost criteria, where lower values represent greater preference, the theoretical utility is defined as:

$$R_{ij} = \frac{X_{ij} - X_{min}}{X_{max} - X_{min}} \quad (3)$$

In this study, Equation (3) is not executed directly because all original cost variables were transformed into standardized preference scores beforehand, allowing Equation (2) to be uniformly applied across all criteria. Finally, the overall utility value $U(ai)$ for each alternative is computed using the additive linear weighting formulation:

$$U_{ai} = \sum_{j=1}^{m} w_j \; x \; R_{ij} \quad (4)$$

Where $U(ai)$ denotes the total utility score of alternative i, wj is the normalized weight of criterion j, and Rij is the corresponding utility value. The alternative yielding the highest overall utility value $U(ai)$ represents the optimal pollination strategy. Criterion weights were determined through structured expert judgment involving plantation managers and Seed Garden supervisors at PT. Bakrie Sawit Unggul in accordance with operational priorities and standard operating guidelines (Nasyuha *et al.*, 2025; Taherdoost & Madanchian, 2023; Taherdoost & Mohebi, 2024). Among the evaluated parameters, pollination success rate received the highest priority weight due to its decisive impact on commercial seed viability and productivity.

4. Results and Discussion

4.1 Results

The decision-making process began by establishing the operational evaluation criteria and their relative importance weights for selecting the most appropriate pollination method for superior oil palm seedlings at PT. Bakrie Sawit Unggul. Five operational criteria were formulated based on standard operating procedures and expert consultations, as detailed in Table 3.

Table 3. Evaluation Criteria and Assigned Weights for Pollination Assessment

Code	Criteria	Type	Weight
C1	Number of Flowers Pollinated	Benefit	0.30
C2	Pollination Success Rate	Benefit	0.25
C3	Processing Time	Cost	0.15
C4	Labor Requirement	Cost	0.15
C5	Pollination Failure Rate	Cost	0.15
Total			1.00

Note. Initial criterion classification prior to standardized preference conversion.

Ten pollination alternatives currently implemented across Seed Garden operations were evaluated. These alternatives encompass conventional practices, scheduled methods, and standardized operational procedures, as presented in Table 4.

Table 4. Evaluated Oil Palm Pollination Alternatives

Code	Pollination Alternative	Description
A1	Manual Pollination	Conventional manual pollination without SOP
A2	Semi-Manual Pollination	Semi-manual execution using standard handheld tools
A3	Scheduled Pollination	Periodic pollination based on regular timetable

A4	Standard SOP Pollination	Standardized pollination guided by company SOP
A5	Intensive Pollination	High-frequency manual pollination
A6	Manual Pollination + SOP	Conventional manual pollination assisted by SOP
A7	Semi-Manual Pollination + SOP	Semi-manual pollination combined with strict SOP
A8	Scheduled Pollination + SOP	Timetable-based pollination combined with strict SOP
A9	Intensive Scheduled Pollination	High-frequency scheduled pollination
A10	Intensive Pollination + SOP	High-frequency pollination reinforced by strict SOP

Note. Operational pollination options tested in Seed Garden management.

Empirical performance data for the ten alternatives across all evaluation criteria were gathered through field observations and operational records, as summarized in Table 5.

Table 5. Initial Operational Data of Pollination Alternatives

Code	Pollination Alternative	C1 (Flowers)	C2 (%)	C3 (Hours)	C4 (Persons)	C5 (%)
A1	Manual Pollination	30	83	3	2	17
A2	Semi-Manual Pollination	32	88	3	2	12
A3	Scheduled Pollination	30	90	2	2	10
A4	Standard SOP Pollination	33	91	2	2	9
A5	Intensive Pollination	34	93	3	3	7
A6	Manual Pollination + SOP	31	85	3	2	15
A7	Semi-Manual Pollination + SOP	33	89	2	2	11
A8	Scheduled Pollination + SOP	34	92	2	2	8
A9	Intensive Scheduled Pollination	35	94	2	3	6
A10	Intensive Pollination + SOP	36	95	2	3	5

Note. Data collected from field documentation at PT. Bakrie Sawit Unggul (2025).

To enable multi-criteria comparison across differing physical units (percentages, counts, hours, and worker numbers), raw operational values were converted into a 1–5 preference scale based on plantation benchmarks. A score of 5 reflects optimal performance, while 1 indicates the least favorable condition. Table 6 provides the conversion guidelines.

Table 6. Sub-Criteria Rating Conversion Guidelines

Score	C1: Flowers Pollinated	C2: Success Rate (%)	C3: Processing Time (Hours)	C4: Labor Requirement (Persons)	C5: Failure Rate (%)
5	≥ 36	≥ 95	2	2	≤ 5
4	34–35	91–94	3	3	6–8
3	32–33	87–90	4	4	9–11
2	30–31	83–86	5	5	12–14
1	< 30	< 83	> 5	> 5	> 14

Note. Operational parameters converted to a standardized five-point preference scale.

Applying these conversion rules to the initial empirical data yielded standardized sub-criteria scores for each alternative, as presented in Table 7.

Table 7 Converted Sub-Criteria Scores of Alternatives

Alternative	C1	C2	C3	C4	C5
A1	2	2	4	5	1
A2	3	3	4	5	2
A3	3	2	5	5	3
A4	4	4	5	5	3
A5	4	4	4	4	4
A6	2	3	4	5	1
A7	3	4	5	5	3
A8	4	4	5	5	4
A9	4	5	5	4	4
A10	5	5	5	4	5

Note. Scaled ratings ready for utility normalization.

Because operational processing time (C3), labor requirement (C4), and failure rate (C5) were mapped such that higher scale values represent shorter durations, lower manpower, and reduced defects, all five criteria operate as benefit criteria in the SMART linear utility model. The minimum ($Xmin$) and maximum ($Xmax$) values across alternatives are outlined in Table 8.

Table 8. Minimum and Maximum Values for Utility Normalization

Criterion	Xmin	Xmax
C1	2	5
C2	2	5
C3	4	5
C4	4	5
C5	1	5

Note. Boundary parameters derived from converted alternative scores.

Using Equation (2), the utility value Rij was calculated for each alternative. For instance, the normalization for Alternative A1 with score vector (2, 2, 4, 5, 1) is computed as follows:

$$R11 = \frac{2-2}{5-2} = \frac{0}{3} = 0.000$$

$$R12 = \frac{2-2}{5-2} = \frac{0}{3} = 0.000$$

$$R13 = \frac{4-4}{5-4} = \frac{0}{1} = 0.000$$

$$R14 = \frac{5-4}{5-4} = \frac{1}{1} = 1.000$$

$$R15 = \frac{1-1}{5-1} = \frac{0}{4} = 0.000$$

Yielding the normalized utility vector A1 = (0.000, 0.000, 0.000, 1.000,0.000) Similarly, for Alternative A2 with score vector (3, 3, 4, 5, 2), the normalization yields:

$$R21 = \frac{3-2}{5-2} = \frac{1}{3} = 0.333$$

$$R22 = \frac{3-2}{5-2} = \frac{1}{3} = 0.333$$

$$R23 = \frac{4-4}{5-4} = \frac{0}{1} = 0.000$$

$$R24 = \frac{5-4}{5-4} = \frac{1}{1} = 1.000$$

$$R25 = \frac{2-1}{5-1} = \frac{1}{4} = 0.250$$

Resulting in the normalized utility vector A2 = (0.333, 0.333, 0.000, 1.000, 0.250). The complete normalization matrix for all ten alternatives is detailed in Table 9.

Table 9 Normalized Utility Matrix of Alternatives

Alternative	C1	C2	C3	C4	C5
A1	0.000	0.000	0.000	1.000	0.000
A2	0.333	0.333	0.000	1.000	0.250
A3	0.333	0.000	1.000	1.000	0.500

A4	0.667	0.667	1.000	1.000	0.500
A5	0.667	0.667	0.000	0.000	0.750
A6	0.000	0.333	0.000	1.000	0.000
A7	0.333	0.667	1.000	1.000	0.500
A8	0.667	0.667	1.000	1.000	0.750
A9	0.667	1.000	1.000	0.000	0.750
A10	1.000	1.000	1.000	0.000	1.000

Note. Matrix elements represent normalized linear utility values Rij.

Following normalization, the overall utility value $U(ai)$ was computed using Equation (4) by multiplying normalized utilities by criterion weights (w1=0.30, w2=0.25, w3=0.15, w4=0.15, and w5=0.15). For Alternative A1, the final utility is:

U(A1)=(0.30)(0.000)+(0.25)(0.000)+(0.15)(0.000)+(0.15)(1.000)+(0.15)(0.000)=0.1500

For Alternative A2, the calculation is:

U(A2)=(0.30)(0.333)+(0.25)(0.333)+(0.15)(0.000)+(0.15)(1.000)+(0.15)(0.250)=0.3707

The complete ranking of pollination alternatives based on their SMART preference scores is presented in Table 10.

Table 10. Final SMART Preference Scores and Ranking of Pollination Alternatives

Rank	Alternative	Description	SMART Score
1	A10	Intensive Pollination + SOP	0.8500
2	A8	Scheduled Pollination + SOP	0.7794
3	A4	Standard SOP Pollination	0.7419
4	A9	Intensive Scheduled Pollination	0.7126
5	A7	Semi-Manual Pollination + SOP	0.6417
6	A5	Intensive Pollination	0.4794
7	A3	Scheduled Pollination	0.4749
8	A2	Semi-Manual Pollination	0.3707
9	A6	Manual Pollination + SOP	0.2333
10	A1	Manual Pollination	0.1500

Note. Higher scores denote greater overall suitability for Seed Garden operations.

The decision model was integrated into a web-based decision support system developed using PHP and MySQL. After authentication, the system presents a primary dashboard comprising six core modules: Home, Criteria Management, Alternative Management, Evaluation Data, SMART Calculations, and Ranking Reports, as illustrated in Figure 2.

Figure 2. Main System Interface

The computational engine executes the automated conversion, normalization, and linear weighting routines, presenting the final evaluation scores and prioritized recommendations on a dedicated calculation report interface, as shown in Figure 3. This automated reporting functionality provides plantation supervisors with transparent, reproducible, and verifiable analytical outputs to guide field operations.

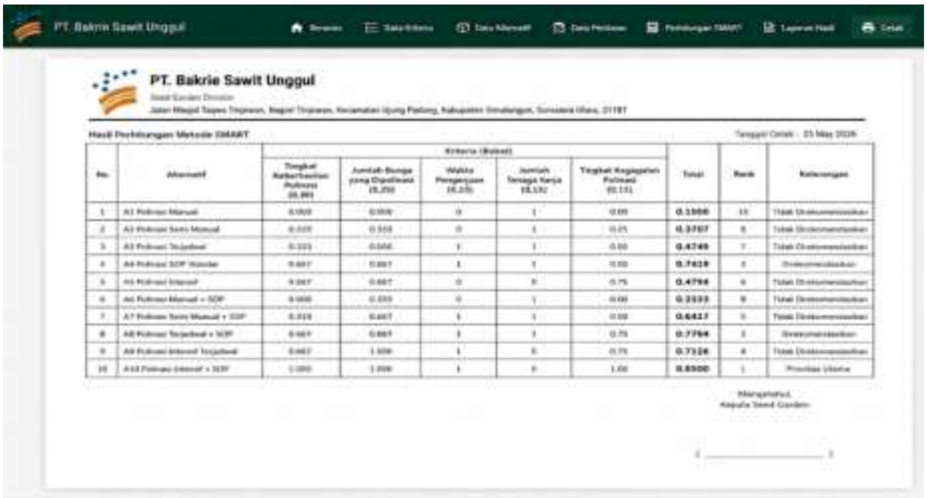

Figure 3. Calculation Report Interface

4.2 Discussion

The computational results generated by the SMART method demonstrated clear discrimination among the ten pollination strategies. Alternative A10 (Intensive Pollination + SOP) achieved the highest overall preference score of 0.8500, indicating optimal performance across all evaluated operational parameters. This alternative achieved maximum utility values on number of flowers pollinated ($R_{10,1}$=1.000), pollination success rate ($R_{10,2}$=1.000), processing time ($R_{10,3}$=1.000), and failure rate reduction ($R_{10,5}$=1.000). Although its labor requirement utility was lower ($R_{10,4}$=0.000) due to requiring three workers instead of two, the substantial gains in biological success and operational throughput clearly outweighed the marginal increase in labor allocation. The ranking order further underscores the vital importance of procedural standardization in plantation workflows. All alternatives integrated with standard operating procedures (A10, A8, A4, and A7) consistently occupied the upper tiers of the ranking, whereas conventional manual pollination without SOP (A1) ranked lowest with a utility score of 0.1500. This stark contrast confirms that human experience alone is insufficient to ensure consistent pollination quality; enforcing structured operational protocols directly mitigates failure rates and elevates seedling viability. These empirical findings align closely with prior studies indicating that multi-criteria decision systems substantially enhance objectivity, operational consistency, and decision quality in agricultural management (Munir & Rahardiyanto, 2023). Methodologically, the implementation corroborates the observations of Taherdoost and Mohebi (2024), who highlighted that the SMART method provides an exceptionally transparent, computationally efficient, and intuitive framework for operational decision-making. Unlike pairwise comparison techniques that often encounter consistency issues when scaling across multiple alternatives, SMART maintains computational stability while delivering clear, reproducible rankings (Nasyuha *et al.*, 2025). From a managerial perspective, the web-based DSS transitions Seed Garden management at PT. Bakrie Sawit Unggul from subjective, experience-based judgments to an objective, data-driven operational model. Digital recording and automated multi-criteria evaluation enable supervisors to standardize daily field execution, allocate labor efficiently, and maintain high standards of superior seed production. Despite these positive outcomes, this study has several limitations that warrant consideration. The evaluation criteria, baseline thresholds, and importance weights were derived through expert judgment within a single plantation company, which may introduce contextual bias. Furthermore, discretizing continuous field data into a 1–5 preference scale involves fixed threshold boundaries that could affect ranking sensitivity under differing operational conditions. Future investigations should conduct systematic sensitivity analyses on criterion weights, validate the model using multi-site empirical datasets from diverse agro-climatic zones, and compare SMART outcomes with hybrid multi-criteria approaches, such as AHP-TOPSIS or PROMETHEE, to further evaluate the generalizability and robustness of the decision framework.

5. Conclusion and Recommendations

This study successfully developed and implemented a web-based smart agritech Decision Support System utilizing the Simple Multi-Attribute Rating Technique (SMART) to determine the optimal pollination strategy for superior oil palm seedlings at PT. Bakrie Sawit Unggul. By evaluating five operational criteria—number of flowers pollinated, pollination success rate, processing time, labor requirement, and pollination failure rate—the proposed framework provides an objective and measurable decision-making mechanism that overcomes the subjectivity and inconsistency of conventional field practices. The computational evaluation identified Alternative A10 (Intensive Pollination + SOP) as the optimal pollination method with the highest preference utility score of 0.8500, followed by Alternative A8 (Scheduled Pollination + SOP) with 0.7794, and Alternative A4 (Standard SOP Pollination) with 0.7419. These results confirm that reinforcing pollination practices with standardized operating procedures substantially mitigates operational defects and enhances biological success. Furthermore, the web application developed with PHP and MySQL streamlines daily operational records, automates utility calculations, and delivers reproducible decision reports to improve Seed Garden management. Nevertheless, this study is subject to several limitations. The evaluation criteria, preference scale thresholds, and weighting distributions were derived from expert consensus within a single plantation site, which may reflect specific localized conditions. To expand the applicability and robustness of the decision framework, future research should conduct systematic sensitivity analyses on criterion weights and preference transformation scales. Additionally, benchmarking the SMART method against other multi-criteria decision-making frameworks, such as AHP, TOPSIS, and PROMETHEE, along with empirical validation across multi-site commercial plantations with varying agro-climatic conditions, will be essential to ensure greater model generalizability.

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