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Decision Support System For Employee Bonus Allocation At Pt. Pesta Pora Abadi Using Multi-Attribute Utility Theory (MAUT)

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ABSTRACT

Employee bonus allocation is a recurring human-resource decision in which multiple performance dimensions must be considered simultaneously. At PT. Pesta Pora Abadi, the existing process relies substantially on manual recapitulation and managerial judgment, creating risks of inconsistent weighting, limited auditability, and avoidable calculation errors. This study develops a desktop-based Decision Support System (DSS) using Multi-Attribute Utility Theory (MAUT) to structure employee bonus decisions across five criteria: discipline, work quality, responsibility, teamwork, and absenteeism. The research combines observation, interviews, literature analysis, requirements engineering, Unified Modeling Language (UML)-based system design, MAUT implementation, and black-box functional testing. MAUT converts heterogeneous criterion values into a common 0–100 utility scale and aggregates them using criterion weights that sum to one. Using an illustrative dataset of five employees, the model produced aggregate utilities of 79.67, 61.46, 61.28, 41.56, and 10.50, with Citra Ayu ranked first. A one-at-a-time sensitivity analysis with ±10% and ±20% perturbations of each criterion weight showed that the first-ranked and last-ranked alternatives remained stable across all scenarios, although the second and third positions were sensitive to modest changes in several weights. The findings indicate that the proposed DSS can make bonus calculations more explicit, reproducible, and traceable while also revealing where managerial weight choices materially affect middle-rank alternatives. The study therefore contributes not only an operational MAUT implementation but also a robustness-oriented interpretation that is relevant to transparent human-resource decision support.

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1. INTRODUCTION

Digital transformation has moved decision support from a specialized analytical function into routine organizational processes. Human-resource management is one of the domains in which this shift is particularly important because many decisions involve heterogeneous evidence, repeated assessments, and consequences that must be explained to employees. Employee bonus allocation is a representative case. A bonus decision can depend on work quality, behavioral performance, discipline, attendance, responsibility, and team contribution, while managers must also ensure that the final decision can be communicated and defended. Traditional manual procedures are vulnerable to inconsistent data aggregation, arithmetic errors, undocumented trade-offs, and a

tendency to overemphasize criteria that are cognitively salient at the time of evaluation. Decision Support Systems (DSSs) are intended to reduce these weaknesses by combining structured data, analytical models, and user-facing interfaces without replacing managerial responsibility [1]. In the Indonesian DSS literature, the same principle is frequently emphasized: a DSS assists decision makers in semi-structured problems by making criteria, alternatives, and calculation logic explicit [2].

At PT. Pesta Pora Abadi, bonus determination has been conducted through a predominantly manual process. Performance information is recapitulated for several criteria, but the final judgment has historically depended heavily on managerial intuition rather than a standardized mathematical aggregation rule. Such a process does not necessarily imply poor judgment; experienced managers can recognize contextual information that is difficult to encode numerically. The problem is that intuitive aggregation is difficult to reproduce consistently across periods, employees, branches, or decision makers. It also complicates procedural transparency because an employee may observe the final bonus decision without being able to reconstruct how differences in discipline, work quality, responsibility, teamwork, and absenteeism were combined. A DSS is therefore valuable not because it automates managerial authority, but because it records the evaluative structure through which managerial preferences are translated into a reproducible calculation.

Multi-Criteria Decision Making (MCDM) provides a natural analytical foundation for this class of problem. MCDM methods are designed for decisions in which alternatives are assessed against multiple, potentially conflicting criteria. Multi-Attribute Utility Theory (MAUT) is especially relevant when the aim is to express heterogeneous criterion values on a common utility scale and combine them through explicit importance weights. Fishburn's work on additive utilities established a formal basis for representing multi-attribute preferences when appropriate assumptions are satisfied [3]. Subsequent reviews have shown that multiattribute utility and broader MCDM research remain central to structured decision analysis, particularly when decision makers must expose trade-offs among attributes rather than rely on a single raw indicator [4]. A contemporary taxonomy of MCDA practice likewise highlights the importance of problem formulation, construction of the recommendation, and traceability of technical support [5]. These characteristics align directly with the requirements of a bonus-allocation system: criteria must be defined, measurement direction must be clarified, weights must be visible, and the effect of each input on the final recommendation must be auditable.

MAUT has several practical properties that fit employee-performance assessment. First, it accommodates criteria measured on different ranges by transforming them into dimensionless utility values. Second, it can distinguish benefit criteria, for which higher values are preferred, from cost criteria, for which lower values are preferred. Third, the additive aggregation model is readily explainable to nontechnical users because a final utility score can be decomposed into criterion-level contributions. Fourth, criterion weights can be adjusted when organizational policy changes, while the underlying computational structure remains the same. These advantages do not eliminate all subjectivity. Weight elicitation itself is a preference judgment, and a linear utility transformation may not capture threshold effects, diminishing returns, or asymmetric managerial preferences. A scientifically defensible implementation must therefore separate what the algorithm computes from what management chooses and should assess whether plausible changes in those choices alter the ranking.

Prior research demonstrates that MAUT has been used in employee and performance-evaluation settings. Khair et al. applied MAUT to employee performance appraisal and showed how several performance dimensions could be converted into a single decision score [6]. Neti implemented MAUT for employee performance appraisal in a government context, illustrating its use for structured ranking across heterogeneous employee characteristics [7]. Kayati et al. applied MAUT in an educational decision-support setting, further demonstrating the method's ability to combine weighted criteria in a transparent ranking framework [8]. Fikri et al. used MAUT for teacher-performance evaluation and reported both black-box and user-acceptance testing of a web-based DSS [9]. These studies reinforce the practicality of MAUT, but they also reveal a common pattern in applied DSS research: emphasis is frequently placed on implementation and ranking output, whereas the stability of the ranking under plausible changes in criterion importance is less often examined.

Research that focuses specifically on employee recognition and reward reaches similar conclusions. Maitasari and Farisi developed a MAUT-based DSS for selecting the best employee and emphasized the reduction of ad hoc subjective judgment [10]. Theo et al. applied MAUT to employee bonus decisions and framed transparency as a response to dissatisfaction associated with unilateral managerial decisions [11]. Wulandari used MAUT for annual teacher rewards [12], while Zulfikar and Chotijah combined AHP and MAUT to separate weighting from final employee-performance ranking [13]. Collectively, these studies support the use of formal MCDM structures for reward allocation. However, they also motivate a distinction between computational objectivity and normative objectivity. An algorithm may calculate consistently from specified inputs, but the choice of criteria, weights, scoring scales, and utility functions remains organizational and must be justified. The present study therefore avoids claiming that MAUT removes subjectivity altogether; instead, it makes the location and consequences of subjective choices more explicit.

Bonus-allocation studies using other MCDM methods provide an important comparative context. Andriani and Meiriza used the Simple Multi Attribute Rating Technique (SMART) for annual employee bonuses [14]. Felicia et al. developed a web-based bonus DSS using weighted-product and weighted-sum approaches [15], while Sofyan et al. applied Simple Additive Weighting (SAW) to web-based employee bonus determination [16]. Mahmudiyah et al. used the Multi-Attribute Border Approximation Area Comparison (MABAC) method for employee bonus decisions [17]. These studies show that employee bonus allocation is not intrinsically tied to one algorithm. Rather, the methodological choice should be connected to the structure of the problem, explainability requirements, data characteristics, and the need for sensitivity analysis. MAUT is attractive in the present case because the organization requires a transparent utility-based aggregation model that can represent both benefit and cost criteria within a single scoring scheme.

Broader employee-evaluation research also supports the use of multi-criteria frameworks. Sumarno et al. evaluated employee performance using MCDM and system-dynamics concepts in a public-sector setting [18]. Derebewa et al. used a fuzzy-logic DSS for hospital employee performance evaluation, illustrating how structured decision models can address ambiguity in human-performance assessment [19]. These studies are methodologically different from the present work, but they underscore a shared challenge: employee performance is inherently multidimensional, and a decision-support model is most useful when it clarifies rather than conceals the assumptions used to aggregate evidence.

The present study addresses a practical and methodological gap in the PT. Pesta Pora Abadi context. Practically, the company requires a repeatable method for transforming five performance indicators into a ranked bonus recommendation and a software system that can document the calculation. Methodologically, a ranking alone is insufficient for evaluating the reliability of a decision model. A very small score difference between two employees can be reversed by modest changes in criterion weights, whereas a large score gap may remain stable under the same perturbations. Consequently, this study extends the original MAUT implementation with a one-at-a-time weight-sensitivity analysis. This analysis does not create new employee observations; instead, it evaluates how robust the illustrative ranking is to reasonable variation in the managerial weighting scheme.

The study makes four contributions. First, it formalizes the bonus-allocation problem as a five-criterion MAUT model containing four benefit criteria and one cost criterion. Second, it implements the model in a desktop DSS using Java NetBeans and a MySQL/MariaDB database. Third, it documents the full transformation from raw values to normalized utilities and aggregate scores so that each ranking position is traceable. Fourth, it evaluates ranking stability under ±10% and ±20% perturbations of each criterion weight while proportionally renormalizing the remaining weights. In doing so, the work moves beyond the common practice of reporting a single ranking and provides evidence about which parts of the ranking are robust and which require careful managerial interpretation. Following the conceptual literature on MAUT, the system is treated as a decision aid rather than an autonomous decision maker; the quality of its recommendation depends on the validity of criteria, measurement procedures, weights, and utility assumptions [20].

Table 1. Positioning of selected prior studies

Study	Method	Application	Main relevance to this study
Khair et al. [6]	MAUT	Employee performance	Utility-based aggregation of multiple performance criteria
Neti [7]	MAUT	Employee appraisal	Structured ranking for employee evaluation
Fikri et al. [9]	MAUT	Teacher performance	DSS implementation with functional/user testing
Maitasari and Farisi [10]	MAUT	Best employee	Reduces reliance on unstructured subjective selection
Theo et al. [11]	MAUT	Employee bonus	Directly related bonus-allocation context
Andriani and Meiriza [14]	SMART	Annual bonus	Alternative additive MCDM approach
Felicia et al. [15]	WP/WSM	Employee bonus	Alternative web-based bonus DSS
Mahmudiyah et al. [17]	MABAC	Employee bonus	Alternative ranking mechanism for reward decisions

Source: Synthesized from the cited literature.

A review of the cited studies indicates that applied employee-reward DSS research is dominated by three outputs: system implementation, a final ranking, and functional testing. Those outputs are necessary but do not fully answer whether the recommendation is robust to plausible managerial preference changes. In additive MCDM models, two alternatives may obtain almost identical total scores even though their criterion profiles differ substantially. Under such conditions, a small change in one weight can reverse their ordering without any change in employee performance data. If the system communicates only the final ordinal rank, users may interpret a fragile numerical distinction as a strong decision. The analytical novelty of the present work is therefore not a new MAUT equation; it is the integration of ranking robustness into the interpretation of an operational MAUT-based bonus DSS. This is important because the value of a decision-support model lies not only in producing an answer but also in showing how dependable that answer is under defensible alternative assumptions.

The study also distinguishes between algorithmic consistency and fairness. MAUT guarantees that a fixed dataset, weight vector, and utility specification will be processed consistently, but fairness additionally depends on the legitimacy of the criteria, the quality of measurement, the transparency of weights, and the organizational consequences of the decision. Accordingly, the proposed framework treats sensitivity analysis as part of decision governance rather than as a purely mathematical exercise. Stable rank positions can be communicated with greater confidence, whereas unstable positions should trigger managerial review, additional evidence, or a tie-handling protocol. This interpretation is particularly relevant for bonus decisions because compensation outcomes are salient to employees and can influence perceptions of procedural justice. The expanded manuscript therefore frames the DSS as an auditable socio-technical process in which software, data, managerial preferences, and explanation are all necessary components of a defensible recommendation.

2. METHOD

This research used a design-and-evaluation approach centered on the development of a computational DSS. The empirical context was PT. Pesta Pora Abadi, where information about employees, performance criteria, current bonus procedures, and managerial preferences was collected through observation and interviews with Human Resources Department (HRD) personnel and company management. Literature analysis was used to establish the conceptual basis of DSS and MAUT and to compare the proposed model with related employee-evaluation and bonus-allocation studies. The study did not treat the illustrative five-employee matrix as a statistically representative sample of the entire workforce. Its purpose was to demonstrate, verify, and discuss the MAUT computation that the software executes. This distinction is important because algorithmic correctness and population-level empirical generalization are different forms of evidence.

The development procedure comprised problem identification, requirements analysis, identification of alternatives and criteria, weight definition, MAUT modeling, UML-based system design, implementation, functional testing, and analytical interpretation of the ranking. UML models included use-case, activity, sequence, and class diagrams. The application was developed with Java NetBeans and connected to a MySQL/MariaDB database using XAMPP. Black-box testing was selected to verify whether user-facing functions behaved according to specified input-output requirements. In the present expanded analysis, a sensitivity-analysis stage was added after calculation of the baseline ranking to examine whether moderate changes in criterion weights changed the ordering of alternatives.

2.1 Criteria and Weight Structure

Five evaluation criteria were defined from the observed company process and management interviews. Discipline (C1), work quality (C2), responsibility (C3), and teamwork (C4) are benefit attributes because higher scores are preferable. Absenteeism (C5) is a cost attribute because fewer absent days are preferable. The baseline criterion weights sum to 1.00. Work quality receives the largest weight (0.25), while teamwork receives the smallest (0.15); the remaining criteria each receive 0.20. The use of fixed baseline weights enables consistent computation across employees, while their explicit representation makes subsequent sensitivity analysis possible.

Table 2. Employee performance criteria and baseline weights

No.	Criterion	Type	Weight	Code
1	Discipline	Benefit	0.20	C1
2	Work quality	Benefit	0.25	C2
3	Responsibility	Benefit	0.20	C3
4	Teamwork	Benefit	0.15	C4
5	Absenteeism	Cost	0.20	C5

Source: Authors' calculation.

2.2 MAUT Normalization and Aggregation

MAUT requires criterion values to be represented on a comparable utility scale before weighted aggregation. For a benefit criterion, the minimum observed value is mapped to 0 and the maximum observed value is mapped to 100. Intermediate values are transformed linearly. For a cost criterion, the direction is reversed so that a lower raw value yields a higher utility. The benefit utility function is:

$$u(a_{ij}) = [(x_{ij} - x_j,min) / (x_j,max - x_j,min)] \times 100$$

For a cost criterion, the utility function is:

$$u(a_{ij}) = [(x_j,max - x_{ij}) / (x_j,max - x_j,min)] \times 100$$

where $u(a_{ij})$ is the utility of alternative i on criterion j, x_{ij} is the observed criterion value, and x_j,min and x_j,max are the minimum and maximum observed values for criterion j. After normalization, the aggregate utility of each employee is calculated as:

$$U(a_i) = \Sigma_j \, w_j \, u(a_{ij}), \quad with \quad \Sigma_j \, w_j = 1$$

The additive structure assumes that criterion contributions can be combined according to their assigned weights. In operational terms, each employee's total score can be decomposed into five weighted utility contributions, which makes the final result easy to audit. The highest total utility is interpreted as the highest bonus priority. The method does not determine the monetary size of the bonus unless a separate policy maps ranks or utility intervals to specific payment levels.

2.3 System Implementation and Functional Testing

The DSS contains modules for authentication, employee master data, criterion and weight management, periodic performance-score entry, automatic MAUT calculation, ranking, and report generation. Employee records include identifying and organizational fields such as employee ID, name, gender, position, and branch. The calculation module retrieves the selected period's assessment values, determines criterion-specific minimum and maximum values, applies the appropriate benefit or cost utility function, multiplies each normalized utility by its weight, and stores or displays the final score and rank. Reports can be exported to PDF and Microsoft Excel to support managerial review and archival documentation.

Black-box testing evaluates observable system behavior without requiring the tester to inspect source-code internals. Test cases were designed around valid and invalid login attempts, employee-data creation and modification, criterion-weight entry, score submission, MAUT calculation, ranking output, and report generation. The testing objective was functional conformance: a successful test means that the implemented function produces the expected user-visible behavior for the supplied input. This type of testing is appropriate for verifying an operational prototype, although it does not establish usability, long-term reliability, cybersecurity, or organizational impact. Those issues are identified as future evaluation requirements rather than inferred from the black-box results.

2.4 Weight-Sensitivity Analysis

Because criterion weights originate from managerial preference rather than from a statistically estimated parameter model, the robustness of the ranking was examined using one-at-a-time weight perturbations. Each baseline weight was separately decreased by 10% and 20% and increased by 10% and 20%. When one weight was changed, the other four weights were proportionally rescaled so that the total remained equal to 1.00. This procedure generated 20 perturbation scenarios in addition to the baseline. The normalized utility matrix was held constant; only the importance structure changed. For each scenario, aggregate utilities were recomputed and the employee ordering was recorded.

The sensitivity procedure addresses a practical question that the baseline ranking alone cannot answer: would a reasonable change in managerial emphasis materially change the bonus priority? Stability of the first-ranked employee across all scenarios provides stronger evidence for that particular ordering than a single baseline score. Conversely, a rank reversal between two closely scored employees indicates that management should interpret their relative ordering cautiously and may wish to introduce additional evidence, tie-handling

rules, or a more formal weight-elicitation method such as AHP, entropy weighting, or Rank Order Centroid in future versions.

3. RESULTS AND DISCUSSION

3.1 Decision Matrix and Baseline Computation

The illustrative decision matrix contains five employees. C1–C4 are scored on a 0–100 scale, whereas C5 records the number of absent days in one month. The raw values therefore cannot be aggregated directly without either assuming commensurability or first transforming them into a common representation. Table 3 presents the decision matrix used to demonstrate the MAUT procedure.

Table 3. Illustrative employee decision matrix

No.	Employee	C1	C2	C3	C4	C5
1	Ahmad Fauzi (A1)	85	80	82	88	1
2	Budi Santoso (A2)	78	85	80	82	3
3	Citra Ayu (A3)	90	88	85	80	0
4	Dedi Kurniawan (A4)	70	75	78	85	4
5	Eka Putri (A5)	88	82	90	78	2

Source: Authors' calculation.

For C1, the observed minimum and maximum are 70 and 90. Ahmad Fauzi's discipline value of 85 is therefore transformed to $(85-70)/(90-70)\times100 = 75.00$. For C5, the observed minimum and maximum are 0 and 4 absent days. Because absenteeism is a cost criterion, Ahmad Fauzi's one absent day becomes $(4-1)/(4-0)\times100 = 75.00$. The same procedure is applied to each element of the matrix. The normalized utilities are shown in Table 4.

Table 4. Normalized MAUT utility matrix

No.	Employee	u(C1)	u(C2)	u(C3)	u(C4)	u(C5)
1	Ahmad Fauzi (A1)	75.00	38.46	33.33	100.00	75.00
2	Budi Santoso (A2)	40.00	76.92	16.67	40.00	25.00
3	Citra Ayu (A3)	100.00	100.00	58.33	20.00	100.00
4	Dedi Kurniawan (A4)	0.00	0.00	0.00	70.00	0.00
5	Eka Putri (A5)	90.00	53.85	100.00	0.00	50.00

Source: Authors' calculation.

The normalized matrix reveals information that is less obvious in the raw data. Citra Ayu reaches the maximum utility for discipline, work quality, and absenteeism, while also obtaining a moderate responsibility utility. Eka Putri obtains the maximum utility for responsibility and a high discipline utility but receives zero utility for teamwork because her teamwork score is the minimum observed value in this five-person dataset. Ahmad Fauzi obtains the maximum teamwork utility and relatively strong discipline and absenteeism utilities. Dedi Kurniawan obtains the minimum utility on four of five criteria but a relatively high teamwork utility. These patterns demonstrate both a strength and a limitation of range-based normalization: it provides a clear relative scale within the observed sample, but the meaning of zero and 100 is sample-dependent rather than an externally calibrated performance standard.

Applying the baseline weights produces the aggregate utilities shown in Table 5. Ahmad Fauzi's score, for example, is $(0.20\times75.00)+(0.25\times38.46)+(0.20\times33.33)+(0.15\times100.00)+(0.20\times75.00)=61.28$. The same weighted-sum computation is applied to all employees.

Table 5. Baseline MAUT ranking

Rank	Employee	Aggregate utility
1	Citra Ayu (A3)	79.67
2	Eka Putri (A5)	61.46
3	Ahmad Fauzi (A1)	61.28
4	Budi Santoso (A2)	41.56

Rank	Employee	Aggregate utility
5	Dedi Kurniawan (A4)	10.50

Source: Authors' calculation.

Citra Ayu ranks first with an aggregate utility of 79.67. The score is approximately 18.20 points higher than the second-ranked alternative, indicating substantial separation under the baseline weights. The distinction between second and third place is much smaller: Eka Putri's 61.46 exceeds Ahmad Fauzi's 61.28 by only 0.18 points. This narrow margin is analytically important. Reporting only the ordinal ranking could give a false impression that the second-place position is as secure as the first-place position. In reality, the baseline calculation already suggests that small changes in weights or measurement values may reverse the ordering of A5 and A1. A defensible DSS should expose this information rather than present the rank as an unquestionable output.

3.2 Sensitivity of the Ranking to Criterion Weights

The sensitivity analysis confirmed the contrast between robust and fragile parts of the ranking. Across all 20 weight-perturbation scenarios, Citra Ayu remained in first place and Dedi Kurniawan remained in fifth place. Budi Santoso also remained fourth. The only rank changes occurred between Eka Putri and Ahmad Fauzi. Decreasing the importance of discipline, work quality, or responsibility tended to move Ahmad Fauzi above Eka Putri, while increasing those weights restored or strengthened Eka Putri's second-place position. Increasing teamwork also favored Ahmad Fauzi because he has the maximum teamwork utility, whereas Eka Putri has the minimum teamwork utility. Increasing absenteeism likewise favored Ahmad Fauzi relative to Eka Putri because their absenteeism utilities are 75 and 50, respectively.

Table 6. Summary of one-at-a-time weight-sensitivity scenarios

Perturbed criterion	Weight change	Rank 1	Rank 2	Rank 3	Ranks 4–5
C1 Discipline	−20% / −10%	A3	A1	A5	A2 / A4
C1 Discipline	+10% / +20%	A3	A5	A1	A2 / A4
C2 Work quality	−20% / −10%	A3	A1	A5	A2 / A4
C2 Work quality	+10% / +20%	A3	A5	A1	A2 / A4
C3 Responsibility	−20% / −10%	A3	A1	A5	A2 / A4
C3 Responsibility	+10% / +20%	A3	A5	A1	A2 / A4
C4 Teamwork	−20% / −10%	A3	A5	A1	A2 / A4
C4 Teamwork	+10% / +20%	A3	A1	A5	A2 / A4
C5 Absenteeism	−20% / −10%	A3	A5	A1	A2 / A4
C5 Absenteeism	+10% / +20%	A3	A1	A5	A2 / A4

Source: Authors' calculation.

The first-place margin also remained substantial. Among the tested scenarios, the smallest gap between Citra Ayu and the second-ranked employee was approximately 14.91 utility points, occurring when the teamwork weight was increased by 20% and the remaining weights were proportionally renormalized. The largest first-to-second gap was approximately 20.07 points when work quality was increased by 20%. These values indicate that Citra Ayu's first-place position is not an artifact of a single narrowly tuned weight vector within the tested neighborhood. By contrast, the A5–A1 ordering is structurally sensitive because the two employees have complementary strengths and a baseline score difference of only 0.18.

This robustness result changes the interpretation of the decision. The system can reasonably present A3 as a stable first-ranked alternative under the tested weight variations, but it should not describe A5 as unequivocally superior to A1. A practical implementation could flag near-ties, for example when adjacent utility scores differ by less than a management-defined threshold. Such a rule would preserve the computational ranking while prompting additional managerial review for borderline cases. This is particularly important in reward decisions because a mathematically tiny difference may have a disproportionate organizational consequence if it determines eligibility for a scarce bonus.

3.3 Interpretation Relative to Prior MAUT Studies

The baseline result is consistent with the general role of MAUT reported in earlier employee-evaluation studies. Khair et al. [6] and Neti [7] show that MAUT can combine multiple employee-performance attributes into a single ranking value. Fikri et al. [9] similarly demonstrate the feasibility of embedding MAUT

in an information system for performance assessment. The present study confirms these implementation-level properties but extends the interpretation in two ways. First, it explicitly treats the five-person dataset as an illustrative computational example rather than evidence that the system improves organizational outcomes. Second, it examines how weight uncertainty affects the ranking, which is necessary when weights are elicited from managerial policy rather than estimated from an external validation criterion.

The distinction matters because a consistent algorithm is not automatically an objective decision in the philosophical or statistical sense. MAUT ensures that identical inputs and weights produce identical outputs; it does not prove that the selected criteria are complete, that the weights are universally correct, or that a linear utility function captures organizational preferences perfectly. This interpretation is aligned with the broader MAUT literature, which emphasizes preference modeling and trade-offs [3], [4], [20]. For high-stakes HR decisions, transparency should therefore include both the numerical result and the assumptions that produce it.

The proposed system also differs from applications that combine a separate weighting method with MAUT. Zulfikar and Chotijah [13], for example, used AHP and MAUT together. Such hybridization can be advantageous because AHP offers a structured pairwise-comparison process for eliciting criterion importance. The current study retains direct managerial weights because that reflects the operational context and keeps the prototype simple. The sensitivity results, however, show precisely why future work should compare direct weighting with AHP, entropy, ROC, or other approaches. If alternative weighting schemes preserve A3's first-place position but repeatedly exchange A1 and A5, then the organization would have stronger evidence about which decisions are robust and which depend on normative preferences.

3.4 Comparison with Alternative Bonus-Decision Methods

The literature on employee bonuses includes SMART, weighted-product, weighted-sum, SAW, and MABAC models [14]–[17]. These methods differ in normalization, aggregation, and the geometry of preference representation. An additive method such as MAUT is attractive when decision makers require a decomposable total score, because each criterion contributes a directly inspectable weighted utility. Weighted-product approaches introduce multiplicative behavior and can penalize low values differently. MABAC evaluates alternatives relative to a border approximation area, while SAW uses a direct additive normalization framework. The existence of multiple reasonable methods means that algorithm selection should be justified by decision requirements rather than by claiming that one technique is universally superior.

For PT. Pesta Pora Abadi, explainability and auditability were prioritized. The MAUT score can be reconstructed manually from the utility matrix and criterion weights, and the software can display both the intermediate utilities and the final weighted sum. This characteristic is valuable in HR governance because a manager can explain why two employees with similar raw totals may receive different utility contributions. At the same time, the sensitivity analysis reveals that explainability should extend to the weight vector. A transparent interface should therefore show the weights used for each evaluation period and ideally preserve historical versions so that a past ranking can be reproduced exactly.

3.5 System-Level Findings and Practical Implications

The implemented desktop DSS provides a workflow that is materially different from spreadsheet-style or undocumented manual aggregation. Authentication controls access to the application; master-data modules establish a consistent employee and criterion structure; evaluation transactions record period-specific scores; the MAUT engine performs normalization and ranking; and reporting modules produce outputs for managerial review. In functional terms, the system converts a sequence of disconnected manual activities into a repeatable process. This can reduce arithmetic error and processing time, but the more important benefit is provenance: the system can retain which raw values, criterion definitions, weights, and calculation rules produced a given recommendation.

From a governance perspective, three implementation practices are recommended. First, the organization should publish or internally communicate criterion definitions, scoring rubrics, and weighting logic before the evaluation period whenever feasible. This reduces the risk that employees perceive criteria as being adjusted after outcomes are known. Second, score entry should be supported by evidence or standardized rating anchors, especially for behavioral criteria such as teamwork and responsibility. Third, the system should

retain an audit trail of changes to scores and weights. These features are not merely software conveniences; they determine whether a technically correct algorithm becomes an organizationally credible decision process.

The sensitivity analysis also suggests an interface improvement. The system could display a robustness indicator beside each adjacent pair of ranks. For example, the first-ranked alternative in the present illustration is stable across all tested ±20% one-at-a-time weight changes, whereas the second and third alternatives are not. A future version could automatically rerun a predefined sensitivity set and display whether each rank is stable, conditionally stable, or tied within a tolerance. Such a feature would help managers distinguish a strong recommendation from a numerically fragile ordering without requiring them to understand all details of decision-analysis mathematics.

3.6 Managerial and Methodological Implications

The results suggest a practical separation between decisions that can be automated computationally and decisions that should remain explicitly managerial. Normalization, weighted aggregation, rank calculation, archival storage, and generation of reproducible reports are well suited to automation because their rules can be specified and tested. By contrast, the selection of criteria, the interpretation of exceptional circumstances, the approval of criterion weights, and the treatment of near-ties should remain governed by documented organizational policy. This division of responsibility avoids a common failure mode in decision-support implementation, namely treating a numerical score as if it were an autonomous judgment. A well-designed interface should therefore display the score components and relevant warnings, not merely a single rank number.

Methodologically, the near-tie between A5 and A1 illustrates why rank distance should be reported together with rank order. The difference of 0.18 utility points is negligible compared with the 18.20-point gap between A3 and A5 under the baseline model. These two gaps contain qualitatively different information even though both appear as a one-rank difference in an ordinal list. Future versions of the DSS could define a practical indifference threshold, such as a minimum utility gap below which alternatives are classified as statistically or managerially indistinguishable pending additional review. The exact threshold should not be invented by the software developer; it should be established through organizational policy, empirical measurement error, or repeated-rating data. This approach would make the system more faithful to the uncertainty inherent in human-performance assessment and reduce the risk of overinterpreting trivial score differences.

3.7 Limitations and Threats to Validity

Several limitations constrain the interpretation of the results. The first is sample size and representativeness. The five-employee matrix is illustrative and is not large enough to support statistical inference about the company's workforce. The ranking demonstrates the algorithm, not the general performance distribution of PT. Pesta Pora Abadi employees. The second limitation concerns criterion construction. The five criteria are operationally meaningful, but the study does not provide psychometric reliability analysis for behavioral ratings, inter-rater agreement, or evidence that the criteria exhaust all relevant dimensions of performance.

Third, the baseline weights are management-defined. This is acceptable for a policy-oriented DSS, but it means the ranking embeds explicit organizational preferences. The sensitivity analysis partly addresses this limitation by showing which ranking positions persist under moderate weight changes, but it does not identify a uniquely correct weight vector. Fourth, min-max utility normalization is sample-dependent. An employee can receive a utility of zero merely because he or she has the lowest value in the observed group, even if the raw performance level is acceptable by an external standard. Future work could use criterion-specific target functions or piecewise utilities based on organizational benchmarks rather than sample extrema.

Fifth, the utility functions are linear. Real managerial preferences may include thresholds, diminishing returns, or noncompensatory rules. For example, very high work quality may not fully compensate for a severe disciplinary violation in some organizations. Such policies should be modeled explicitly rather than assumed to fit an additive linear structure. Sixth, black-box testing establishes functional behavior but not usability, security, scalability, or causal organizational benefit. A stronger evaluation would combine unit and integration testing, usability assessment with HR users, performance testing on realistic employee volumes, security review, and longitudinal comparison of processing time and decision consistency before and after deployment.

Finally, the study does not compare the final ranking empirically against independent expert judgments or downstream outcomes such as retention, productivity, or future performance. Comparative research could apply MAUT, SAW, SMART, MABAC, TOPSIS, or other methods to the same validated dataset and examine rank correlation, robustness, interpretability, and stakeholder acceptance. The goal should not be to identify a universal winner but to determine which modeling assumptions are most appropriate for the company's decision context.

4. CONCLUSION

This study developed and analyzed a desktop Decision Support System for employee bonus allocation at PT. Pesta Pora Abadi using Multi-Attribute Utility Theory. The system formalizes five performance dimensions—discipline, work quality, responsibility, teamwork, and absenteeism—into an explicit utility-based aggregation process. The baseline weights are 0.20, 0.25, 0.20, 0.15, and 0.20, respectively. Benefit and cost criteria are normalized to a common 0–100 scale, after which weighted utilities are summed to produce a ranking. In the illustrative five-employee dataset, Citra Ayu obtained the highest aggregate utility of 79.67, followed by Eka Putri at 61.46, Ahmad Fauzi at 61.28, Budi Santoso at 41.56, and Dedi Kurniawan at 10.50.

The expanded analysis demonstrates that reporting a single ranking is not sufficient for responsible interpretation. Across 20 one-at-a-time weight-perturbation scenarios, the first, fourth, and fifth positions remained unchanged, while the second and third positions reversed under several plausible changes. This result is particularly important because the baseline difference between the second- and third-ranked employees is only 0.18 utility points. The DSS should therefore be used as a structured decision aid that reveals both ranking outcomes and their sensitivity to managerial assumptions.

From an implementation perspective, the system can improve reproducibility, traceability, and administrative efficiency by integrating employee data, criterion management, assessment input, automated MAUT calculation, ranking, and reporting. However, claims of improved fairness or organizational effectiveness require broader empirical validation. Future studies should use larger primary datasets, standardized scoring rubrics, multiple raters, and longer observation periods; compare alternative weighting strategies; implement target-based or nonlinear utility functions where appropriate; and evaluate usability, security, scalability, and organizational outcomes after deployment. Integrating digital attendance records and existing HR information systems would further reduce manual data entry and support real-time or period-based decision processing.

Overall, the principal value of MAUT in this application is not that it eliminates managerial judgment, but that it makes judgment explicit and computationally inspectable. When criteria, weights, utility functions, and sensitivity results are documented, bonus allocation becomes easier to reproduce, explain, and audit. That combination of analytical transparency and managerial accountability is the central contribution of the proposed DSS.

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