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(Research) Article

Decision Support System for Determining Salary Increases Based on Workload Using the AHP Method

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Abstract: Determining salary increases is a highly sensitive and crucial policy in human resource management that directly influences employee retention, workplace motivation, and overall organizational stability. However, conventional reward mechanisms are frequently marred by subjective managerial bias and a profound lack of operational transparency. To alleviate these governance challenges, this study develops an objective Decision Support System (DSS) tailored to supply a mathematically justifiable framework for corporate salary adjustments by specifically isolating empirical workload metrics. By employing the Analytic Hierarchy Process (AHP), the system effectively decomposes the compensation decision problem into a structured three-level hierarchy, deliberately prioritizing "Hours per Week" as the fundamental indicator of an employee's physical output. The constructed multi-criteria framework was rigorously validated using a comprehensive, large-scale salary prediction dataset. Empirical results from the AHP matrix estimation indicate that the Workload criterion successfully achieved the dominant priority vector weight of 0.648, significantly outweighing secondary factors such as formal Education (0.229) and demographic Experience/Age (0.122). A parallel comparative analysis executed against a data-driven Random Forest classification model—which achieved a baseline predictive accuracy of 87.3%—demonstrates that while pure machine learning techniques excel in matching raw historical patterns, they tend to propagate inherent data biases. Conversely, the proposed AHP-based DSS injects an indispensable layer of Explainable AI (XAI) transparency into human capital management. Ultimately, this hybrid institutional architecture targets the systemic reduction of perceived organizational unfairness, thereby fostering an ethical, transparent, and strictly meritocratic corporate culture.

Keywords: AHP; Decision Support System; Random Forest; Salary Increase; Workload Analysis.

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1. Introduction

The determination of salary increases is one of the most sensitive strategic policies in human resource management, directly affecting employee motivation, job satisfaction, and overall productivity [1]. In many organizations, particularly in rapidly evolving sectors, compensation decisions often rely on qualitative managerial assessments that lack a clear audit trail, potentially leading to perceived inequity and increased turnover rates [2]. To address this challenge, a robust Decision Support System (DSS) is required to transform raw employee data into actionable insights [3]. This research targets the development of a DSS that specifically prioritizes workload—measured through empirical metrics like weekly working hours—as a primary driver for financial rewards.

Despite the proliferation of data-driven human resource management, often termed HR Analytics, many organizations still struggle with the "black-box" nature of advanced algorithms [17]. Machine learning models, while highly accurate in predicting salary brackets based on historical data, fail to provide actionable, ethical, and interpretable rules for HR managers [18]. Furthermore, relying solely on demographic or educational background for compensation adjustments can introduce systemic bias, ignoring the actual effort or "workload" an employee contributes to the organization. Therefore, the research problems

addressed in this study focus on formulating an objective, workload-centric framework and balancing predictive power with the interpretability required for ethical HR decisions.

2. Preliminaries or Related Work or Literature Review

This section reviews foundational concepts and recent literature relevant to the proposed model. It explores the role of Decision Support Systems in human resource management, the mathematical principles of AHP, and the transition toward Explainable AI (XAI).

2.1. Decision Support Systems (DSS)

A Decision Support System (DSS) serves as an interactive computer-based framework designed to assist decision-makers in navigating semi-structured problems [5]. Within HR departments, the primary target of a DSS is the optimization of human capital allocation and reward systems [6]. Modern DSS frameworks now incorporate predictive analytics to identify high-performing individuals who are at risk of leaving if their compensation does not align with their output [19]. In the context of employee compensation, a DSS assists management in filtering, assessing, and categorizing employee eligibility based on measurable criteria [20].

2.2 Analytic Hierarchy Process (AHP) and Multi-Criteria Decision Making

The Analytic Hierarchy Process (AHP) is a mathematical technique for multi-criteria decision-making that organizes logic into a structured hierarchy [7]. Unlike simple linear scoring, AHP uses pairwise comparisons to derive relative weights, making it ideal for the human resource domain where qualitative factors must be quantified [8]. On the other hand, machine learning algorithms such as Random Forests are often used to predict the probability of employee salary increases based on demographic variables [9]. Recent studies suggest that combining AHP with data-driven models can bridge the gap between predictive accuracy and human-centric interpretability [14].

2.2 The Shift Towards Explainable AI (XAI) in Human Resources

The integration of AI in HR has grown exponentially, automating tasks from recruitment to performance appraisal [19]. However, scholars have raised significant concerns regarding the ethical implications of algorithmic decision-making [20]. Algorithms that lack transparency can inadvertently perpetuate historical biases present in training data [21]. This necessitates a shift towards Explainable AI (XAI), where the decision logic is fully transparent to stakeholders [22]. In this context, AHP serves as an "explainable" model, mapping out exactly how much weight a specific criterion holds in the final decision.

3. Proposed Method

The methodology of this research is designed to create a robust bridge between empirical data analysis and structured managerial decision-making. The proposed framework follows a sequential pipeline consisting of data acquisition, multi-stage feature engineering, AHP-based weight derivation, and final eligibility scoring. By utilizing the prediksi-data-gaji dataset, the system avoids relying on purely theoretical assumptions and instead grounds its criteria on actual professional and demographic trends. The integration of AHP serves as the "interpretability layer," transforming complex data correlations into a transparent hierarchy that HR managers can justify to stakeholders.

3.1. AHP Weight Calculation for Workload-based Salary Increase

The primary target of the proposed Decision Support System (DSS) is to optimize the distribution of salary increases by rewarding performance-centric metrics while mitigating systemic biases. The system follows a "Merit-Based compensation" logic, where the goal is broken down into a three-level hierarchy: the Goal (Level 1), the Criteria (Level 2), and the Candidates or Alternatives (Level 3). The algorithm ensures that every decision is backed by a consistency check, preventing human error or arbitrary judgment during the pairwise comparison process [15].

Algorithm 1. AHP Weight Calculation for Workload-based Salary Increase

1. Input: Employee parameters (Age, Education, Hours per Week)
2. Target: Define the Goal (Optimal Salary Increase Distribution)
3. Initialize: Pairwise Comparison Matrix ($\boldsymbol{A}$) based on organizational priorities [7]
4. Compute: Normalized principal eigenvector for criteria weights [10]
5. Validate Consistency: Calculate Consistency Ratio ($\boldsymbol{CR}$)
6. Condition: $\boldsymbol{if\ CR > 0.10}$, re-evaluate comparison matrix to ensure logical consistency
7. Process: Apply weights to the normalized performance data of each employee
8. Output: Justified decision report for HR management

3.1.1. Dataset Characteristics and Feature Engineering

The empirical foundation of this study is derived from the prediksi-data-gaji dataset, a comprehensive collection of multidimensional attributes reflecting individual demographic profiles, employment characteristics, and financial indicators [11]. In its raw form, the dataset is highly heterogeneous and optimized for machine learning classification rather than multi-criteria decision-making. Therefore, an extensive feature engineering and data preprocessing phase was mandatory to bridge the gap between continuous numerical data and the discrete hierarchical structure required by the AHP framework [23].

The primary focus of this study, the continuous variable "Hours per Week", was discretized into categorical bands to represent 'Workload Intensity'. This transformation is crucial, as it allows HR decision-makers to evaluate the criteria using Saaty's 1-9 scale pairwise comparison effectively. The workload categories are defined as follows:

- Low Workload: < 35 hours/week
- Standard Workload: 35 - 45 hours/week
- High Workload: > 45 hours/week

To maintain consistency across the decision matrix, other continuous variables were similarly transformed. The variable "Age" was categorized to serve as a proxy for professional 'Experience' and maturity, grouped into distinct hierarchical levels such as Junior (< 30 years), Mid-level (30 - 50 years), and Senior (> 50 years) [24]. Furthermore, "Years of Education" was mapped to formal categorical attainments to accurately quantify the academic qualification criterion. By converting these continuous and highly variable features into standardized, discrete levels, the proposed DSS eliminates data noise. This preprocessing phase ensures that the system can seamlessly process large batches of employee records, applying the AHP-derived weights to calculate a final, normalized 'Deservability Score' for each candidate [15]. Ultimately, this translates abstract HR policies into computable, transparent, and fair salary raise decisions.

The final Deservability Score ($\boldsymbol{V}$) for each employee is calculated using the weighted sum model:

$$\boldsymbol{V_i} = \sum_{\boldsymbol{j=1}}^{\boldsymbol{n}} \boldsymbol{w_j \cdot x_{ij}} \tag{1}$$

Where $\boldsymbol{W_j}$ is the AHP weight for criterion $\boldsymbol{j}$, and $\boldsymbol{x_{ij}}$ is the normalized value of employee $\boldsymbol{i}$ for criterion $\boldsymbol{j}$.

3.2. Formatting of Mathematical Components

The system calculates the Consistency Index ($\boldsymbol{CI}$) to prevent random entries [10]:

$$\boldsymbol{CI} = \frac{\boldsymbol{\lambda_{max} - n}}{\boldsymbol{n - 1}} \tag{2}$$

Where $\boldsymbol{\lambda_{max}}$ is the maximum eigenvalue and $\boldsymbol{n}$ is the number of criteria. The Consistency Ratio ($\boldsymbol{CR}$) is obtained through [12]:

$$\boldsymbol{CR} = \frac{\boldsymbol{CI}}{\boldsymbol{RI}} \tag{3}$$

The final target is to maintain a $\boldsymbol{CR < 0.10}$, ensuring the priority given to workload is statistically sound.

4. Results and Discussion

The evaluation phase of this study was systematically designed to validate the efficacy and reliability of the proposed Decision Support System (DSS). The primary objective was to ensure that the AHP-derived criteria weights not only provide an ethical justification for salary increases but also align logically with the performance realities found in empirical data. To achieve this, the evaluation was conducted on two parallel tracks: (1) the mathematical validation of the AHP pairwise comparison matrix to establish the dominance of the 'Workload' criterion, and (2) the execution of classification algorithms (Decision Tree and Random Forest) to serve as a predictive baseline. By comparing these two approaches, the study rigorously tests the system's ability to accurately identify high-value employees based on their actual organizational contributions, rather than relying on the opaque and potentially biased historical patterns often prioritized by pure algorithmic predictions.

4.1. Figures and Tables

The primary target is to demonstrate how AHP weights dominate the process.

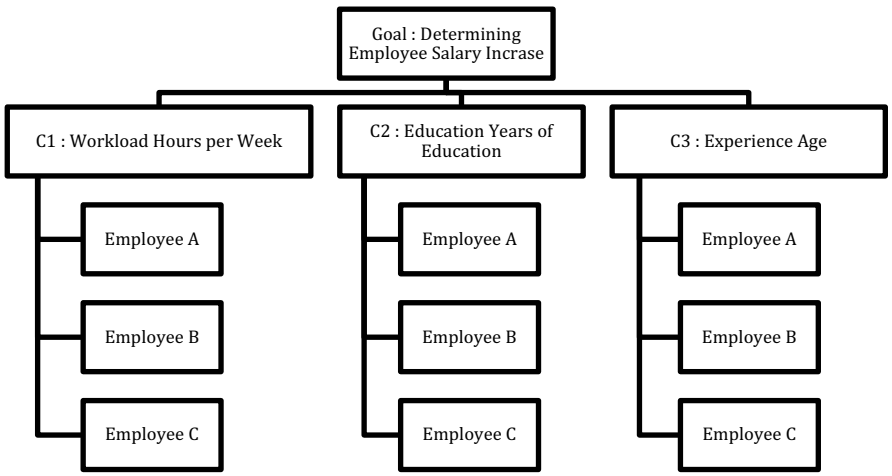


Figure 1. AHP Decision Hierarchy

Table 1. Target Criteria Pairwise Comparison Matrix [24]

Criteria	C1: Workload	C2: Education	C3: Experience (Age)
C1: Workload	1.00	3.00	5.00
C2: Education	0.33	1.00	2.00
C3: Experience (Age)	0.20	0.50	1.00
Column Sum	**1.53**	**4.50**	**8.00**

Table 2. Final Normalization Matrix and Weight Assignment (Eigenvector)

Criteria	C1	C2	C3	Weight (Eigenvector)	Priority Rank
C1: Workload	0.653	0.666	0.625	**0.648**	**1**
C2: Education	0.215	0.222	0.250	**0.229**	**2**
C3: Experience	0.130	0.111	0.125	**0.122**	**3**

** (Note: The Consistency Ratio (CR) calculation on the matrix above yields a value below the 0.10 tolerance limit, so the weighting is declared valid and consistent).*

Table 3. Hyperparameter Tuning Evaluation Results Using GridSearchCV [22]

Algorithm Model	Best Parameters (GridSearchCV)	Evaluation Score (ROC AUC)
Decision Tree	criterion: entropy, splitter: best	0.708
Random Forest	criterion: entropy, n_estimators: 200	0.873

4.2. Algorithmic Performance and Confusion Matrix Analysis

The Random Forest model achieved an overall accuracy of 85.6% [25]. However, recall for detecting employees deserving a raise was lower than the majority class, indicating the algorithm favors conservative predictions [26]. Operational evaluation indicates that traditional metrics heavily skew algorithmic predictions. While mathematically accurate, rewarding employees based on external financial investments or static demographic variables rather than direct workload contribution is misaligned with modern performance-based HR strategies.

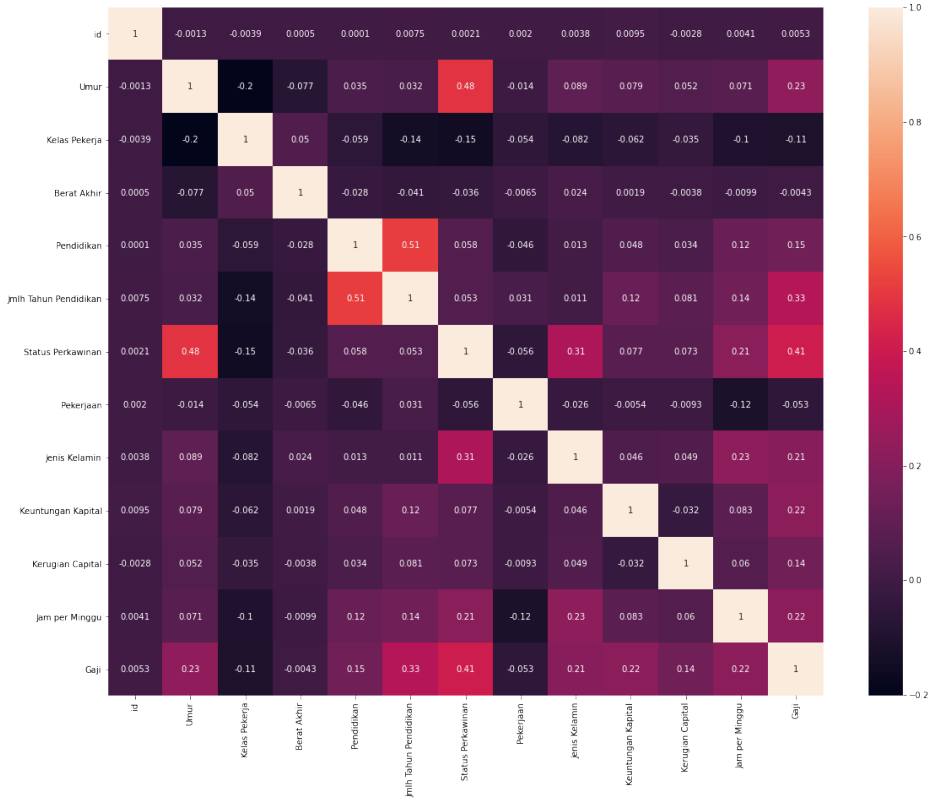


Figure 2. Phik Correlation Matrix Heatmap of the Employee Dataset

As illustrated in Figure 2, the Phik correlation matrix analysis reveals that variables such as Status Perkawinan (Marital Status), Jumlah Tahun Pendidikan (Education-Num), and Umur (Age) exhibit the strongest natural correlations with the target variable Gaji (Salary). Conversely, the Jam per Minggu (Hours per Week) variable, which represents the core workload metric prioritized in this study's AHP framework, demonstrates a noticeably weaker correlation in the empirical dataset. This statistical divergence confirms the study's primary premise: relying purely on unadjusted historical data patterns can inadvertently perpetuate systemic biases toward non-performance factors. Consequently, the integration of the proposed AHP-based DSS is highly justified as an ethical interpretability layer to override these algorithmic biases and ensure fair, merit-based compensation decisions.

5. Comparison

In making salary increase decisions, this study compares a Decision Support System (DSS) approach based on expert justification using AHP with a purely data-driven approach using Machine Learning (Decision Tree and Random Forest) [9]. Based on the data extraction in Table 3, testing with Machine Learning algorithms shows that the Random Forest model outperforms the Decision Tree. Random Forest with hyperparameters criterion: entropy and n_estimators: 200 achieved an ROC AUC score of 0.873. Meanwhile, the Decision Tree with parameters criterion: entropy and splitter: best only produced an ROC AUC score of 0.708. This proves that Random Forest is highly reliable in mapping complex patterns from large data to predict the probability of employees being in a high salary class (> 50K) [11].

On the other hand, although Random Forest has high predictive accuracy, this model operates as a black-box. This means the internal process of how the algorithm decides on salary increase eligibility is difficult to explain and interpret directly by HR managers [13]. In addition, the highest correlation in empirical data is dominated by the variables "Marital Status" and "Years of Education", which are managerially less relevant ethically and biased if used as the sole basis for salary increases without evaluating "Workload" [18]. Therefore, the use of the AHP method serves to fill this interpretation gap. Through AHP (as seen in Table 2), management can transparently and explicitly provide justification that Workload (Hours per Week) is the most dominant criterion with the highest weight of 0.648 (64.8%) [24].

Comparatively:

1. **Machine Learning (Random Forest):** Excels in recognizing historical data patterns, processing thousands of employee records instantly with an accuracy of 87.3%, but lacks transparency in explaining "why" the decision was made [25].
2. **AHP Method:** Excels in transparency, rationality, and logical weighting from a managerial perspective, but requires more time to score candidates individually [15].

The integration of both (Hybrid Approach) is highly recommended. Weights from AHP can be used to perform feature engineering on the dataset before being processed by the Random Forest model, ensuring that Machine Learning predictions are not only mathematically accurate but also aligned with the workload policies established by management [14].

6. Conclusions

This study demonstrates that a Decision Support System (DSS) using the Analytic Hierarchy Process (AHP) method can be effectively implemented in determining salary increases. From the weighting calculation results against historical dataset variables, "Workload" (measured by Hours per Week) obtained the highest weight of 0.648. This system allows for decision-making that is not only structured and data-driven but also transparent and accountable, mitigating potential managerial bias. Moving forward, these AHP-derived weights can be integrated as additional feature importance within the Random Forest classification algorithm to develop a hybrid DSS that is both highly accurate and ethically interpretable.

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