

Enhancing Recruitment Transparency Using Simple Additive Weighting in Smart City Governance

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Abstract. The advancement of digital governance requires municipal recruitment processes that are transparent, accountable, and based on measurable criteria. In many local government environments, recruitment remains manual or semi-structured, increasing subjectivity, reducing efficiency, and limiting the traceability of decision outcomes. Although Decision Support Systems (DSS) using the Simple Additive Weighting (SAW) method are widely applied for candidate ranking, prior work often emphasizes technical scoring accuracy with limited attention to Smart City governance needs such as transparency, auditability, and accountable decision justification. This study develops and evaluates a SAW-based DSS to support objective, transparent, and traceable recruitment decisions within a Smart Governance context. Using a quantitative system development approach, candidate attributes were transformed into numerical scores and assessed through weighted criteria: education, work experience duration, English proficiency, age (cost criterion), and relevance of work experience. The SAW computation produced consistent and interpretable rankings, with the highest preference score reaching 98.462, indicating reduced reliance on unstructured subjective judgment. Usability testing using the System Usability Scale (SUS) yielded an average score of 87.6 ("Excellent"), demonstrating strong acceptance and practical feasibility across stakeholder roles. Overall, the proposed system functions as a governance-support tool that strengthens transparency and accountability in public-sector recruitment.

Keywords: DSS, SAW, Smart Governance, Recruitment, Accountability

1. INTRODUCTION

Employee recruitment is a strategic organizational process aimed at identifying, attracting, and selecting individuals whose qualifications and values align with institutional goals and culture. It is one of the most critical components of strategic human resource management (HRM), directly influencing institutional capability, adaptability, and long-term sustainability [1]. Within public administration, effective recruitment ensures that human capital supports not only operational efficiency but also the ethical and transparent delivery of public services [2]. According to Konateh et al. [3], ineffective or opaque recruitment processes in the public sector may result in mismatched personnel, reduced institutional performance, and weakened public trust. Thus, recruitment quality plays a pivotal role in shaping both organizational outcomes and citizen satisfaction.

In Indonesia, government recruitment systems have increasingly adopted digital technologies in line with national e-government and Smart City initiatives. However, implementation across regions remains uneven, particularly within public-sector human resource management. Several studies report that recruitment processes at the local government level often continue to rely on manual or semi-structured evaluation practices, resulting in fragmented data management, limited transparency, and weak accountability mechanisms [2], [3], [4]. This condition indicates a persistent gap between policy-level digital transformation and its operational realization in recruitment decision-making, especially in processes that directly affect fairness and institutional legitimacy.

Banjarmasin City provides a relevant municipal case for examining the gap between Smart City initiatives and recruitment practices in local governance. Despite this strong digital infrastructure readiness, recruitment practices within local institutions and companies largely remain conventional, relying on manual document processing, subjective assessments, and non-traceable decision mechanisms. This mismatch between digital governance maturity and recruitment practices highlights a specific problem: existing recruitment systems in Banjarmasin are not yet aligned with Smart Governance principles that demand transparency, accountability, and data-driven decision-making.

Algorithmic transparency and accountability are widely recognized as core requirements of Smart City systems, particularly when automated or semi-automated decisions affect citizens' opportunities and rights [5]. In the context of public-sector recruitment, transparent decision logic and traceable evaluation processes are essential to ensure fairness and institutional legitimacy. However, recruitment practices in Banjarmasin currently lack structured mechanisms that enable transparent weighting of criteria and auditable decision outcomes. This limitation indicates the need for decision-support mechanisms that can operationalize algorithmic transparency within recruitment processes.

Smart City governance frameworks increasingly promote the use of Decision Support Systems (DSS) to enhance efficiency, objectivity, and accountability in administrative decision-making. Multi-Criteria Decision-Making (MCDM) methods, including the Simple Additive Weighting (SAW) method, have been widely applied to recruitment due to their simplicity, interpretability, and effectiveness in producing objective rankings [6], [7]. Previous studies report that SAW-based systems improve recruitment accuracy and fairness across various organizational contexts [8], [9], [10], [11]. However, most of these studies are situated in private or corporate environments and primarily emphasize operational efficiency, with limited attention to governance-related dimensions such as transparency, accountability, and decision traceability.

Consequently, there is a clear research gap in the application of SAW-based DSS for public-sector recruitment within Smart City governance frameworks. Existing studies rarely examine how DSS-based recruitment systems contribute to smart governance outcomes, such as transparent decision-making, institutional accountability, and public trust. Empirical evidence remains limited regarding the integration of SAW into municipal recruitment systems that explicitly support governance objectives rather than merely improving technical efficiency. This gap is particularly evident in Indonesian local governments, including Banjarmasin.

Accordingly, this study aims to design, implement, and evaluate a Decision Support System (DSS) employing the Simple Additive Weighting (SAW) method to enhance recruitment transparency within the Smart City governance framework of Banjarmasin. To address the identified research gap, this study makes the following contributions:

- 1) Develops a SAW-based DSS tailored to recruitment processes in a municipal Smart City context.
- 2) Repositions SAW from a purely efficiency-oriented human resource tool into a governance instrument that supports transparency, accountability, and decision traceability.
- 3) Provides empirical evidence of system usability and acceptance through System Usability Scale (SUS) evaluation in public-sector recruitment.

2. METHODS

This study employs a quantitative decision support system (DSS) development approach to enhance objectivity, transparency, and traceability in employee recruitment within the Smart City governance context of Banjarmasin. The chosen research design is aligned with the formulation of the research problem and objectives, which focus on reducing subjectivity and improving accountability in conventional recruitment processes through a structured, data-driven evaluation mechanism. The quantitative approach is appropriate because recruitment decisions involve multiple measurable criteria that can be systematically processed using mathematical models. In this study, qualitative and quantitative applicant attributes are transformed into numerical values and evaluated using the Simple Additive Weighting (SAW) method, a multi-criteria decision-making (MCDM) technique that enables consistent comparison across alternatives. By explicitly representing criteria importance through weighted aggregation, the DSS supports transparent and reproducible decision-making, which is essential in public-sector recruitment and Smart Governance environments.

The research procedure consists of several sequential stages, as illustrated in Figure 1. First, problem identification and literature review are conducted to define the recruitment context and establish a theoretical foundation related to DSS, MCDM, and Smart City governance. Next, recruitment criteria are identified based on relevant literature and practical requirements. Criteria weights are then assigned by domain experts from the human resources (HR) department to reflect organizational priorities for the vacant position. To ensure methodological rigor, the weighting process is explicitly documented, normalized, and later discussed in terms of potential subjectivity and bias. Subsequently, the SAW method is applied through decision matrix construction,

normalization of criteria values, weighted aggregation, and ranking of candidates. The resulting DSS is implemented as a web-based system to support transparent recruitment processes. Finally, system evaluation is conducted using the System Usability Scale (SUS) to assess usability and user acceptance, ensuring that the developed system is not only technically valid but also practically applicable for end users.

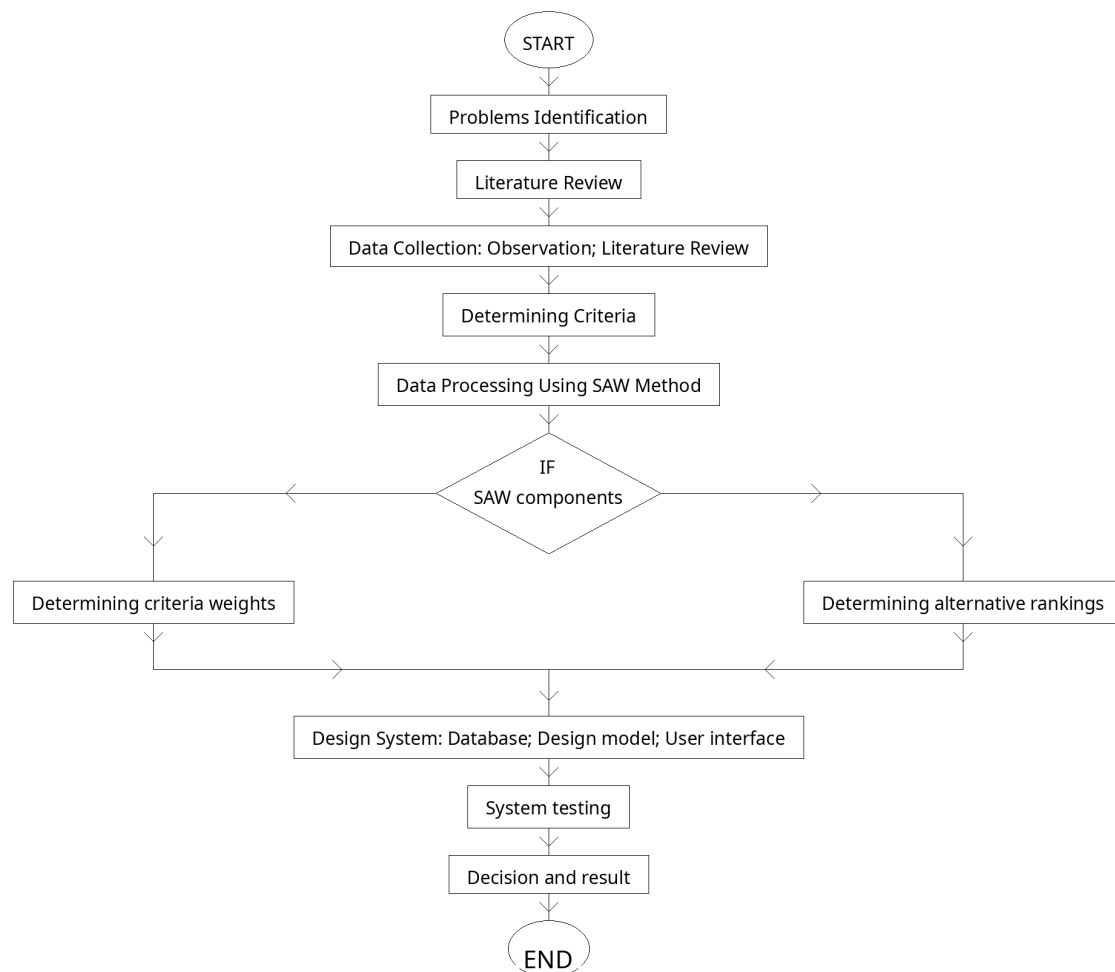


Figure 1. Research Process

2.1 Simple Additive Weighting

Figure 2 illustrates a system flowchart detailing the procedural steps involved in generating recommendations for prospective employees using the SAW method. The process begins with the input of job vacancy information, followed by the identification of relevant criteria names and values associated with the open position. Depending on the evaluation approach, if sub-criteria are utilized, the system prompts the user to

define these sub-criteria. Otherwise, the system proceeds to collect data on the alternative candidates. The core mechanism of the system is the application of the SAW algorithm, which assigns a numerical value to each candidate. This value is calculated based on the degree to which they satisfy the established criteria. The outcome of this computation is a ranked recommendation of the most suitable candidate, thus completing the decision-making process. The following is a flowchart explained in Figure 2.

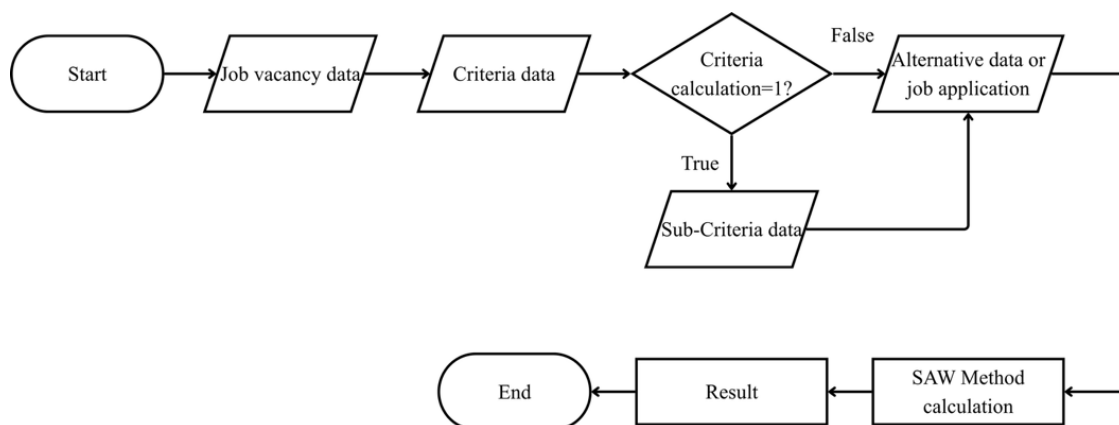


Figure 2. SAW Procedural Steps

The Simple Additive Weighting (SAW) method is a Multi-Criteria Decision-Making (MCDM) technique used to rank alternatives based on the weighted aggregation of multiple evaluation criteria. In this study, SAW is implemented as the core computational mechanism of the Decision Support System (DSS) to support transparent, objective, and traceable recruitment decisions within a Smart City governance context. SAW is selected due to its computational simplicity and high interpretability, which allow decision logic to be clearly understood and audited by stakeholders [12], [13]. This characteristic is particularly important in public-sector recruitment, where decision-making processes must be explainable and accountable. In the proposed system, both qualitative and quantitative applicant attributes are transformed into numerical values, normalized, and aggregated using predefined criteria weights to generate a final ranking of candidates. To ensure methodological clarity and consistency, all symbols and notations used in the SAW formulation are explicitly defined in Table 1.

Table 1. Notation and Symbols Used in the SAW Method

Symbol	Description
A_i	Alternative (candidate) i
C_j	Criterion j
x_{ij}	Original value of alternative i on criterion j
r_{ij}	Normalized value of alternative i on criterion j
w_i	Weight of criterion j
V_i	Final preference value of alternative i
m	Number of alternatives
n	Number of criteria

The SAW implementation in this study follows four sequential steps [6]:

- 1) Step 1. Construction of the initial matrix. An initial matrix $X = [x_{ij}]$ is constructed, where each row represents an alternative and each column represents a criterion. The matrix contains the original performance values of candidates for each criterion.
- 2) Step 2. Normalization of criteria values. To enable comparison across different measurement scales, the decision matrix is normalized. For benefit criteria, higher values indicate better performance, whereas for cost criteria, lower values are preferred. The normalization process is defined as shown in Equation 1.

$$r_{ij} = \begin{cases} \frac{x_{ij}}{\max_{ij}}, & \text{if } C_j \text{ is a benefit criterion} \\ \frac{\min_{ij}}{x_{ij}}, & \text{if } C_j \text{ is a cost criterion} \end{cases} \quad (1)$$

Where r_{ij} represents the normalized performance value of alternative i on criterion j [14].

- 3) Step 3. Weighted aggregation. After normalization, each criterion value is multiplied by its corresponding weight to reflect its relative importance. The final preference value of each alternative is calculated as shown in Equation 2 [15]:

$$V_i = \sum_{j=1}^n w_j \times r_{ij} \quad (2)$$

Where V_i denotes the overall performance score of alternatives i

- 4) Step 4. Ranking of alternatives. The alternatives are ranked based on their final preference values V_i . A higher value of V_i indicates a more suitable candidate for the recruitment decision [16].

By standardizing notation and clearly defining each computational step, the SAW method in this study ensures methodological consistency and transparency. All symbols and formulations introduced in this section are applied consistently in the Results and Discussion section to maintain coherence between methodological explanation and analytical outcomes.

2.2 Data Collection

Selection criteria serve as parameters for evaluating and comparing potential employees. To ensure that the recommended candidates generated by the Decision Support System (DSS) meet organizational requirements, precise and relevant evaluation criteria must be established. The assignment of weights is a critical step in this process, as each criterion is assigned a value reflecting its relative importance in the recruitment decision [17]. The recruitment criteria in this study were identified through a combination of literature review and practical recruitment requirements. To support quantitative processing using the Simple Additive Weighting (SAW) method, most criteria were decomposed into sub-criteria that transform qualitative candidate attributes into numerical values. This transformation enables consistent normalization and aggregation within the SAW framework.

In this study, criteria weights were determined by domain experts from the human resources (HR) department to reflect organizational priorities and job-specific requirements. The involvement of HR experts is justified by their contextual knowledge of recruitment policies, competency standards, and strategic workforce needs relevant to the vacant position. Although expert-based weighting enhances contextual relevance, it may introduce subjective bias. To mitigate this potential bias, the assigned weights were normalized to sum to 100, documented explicitly, and aligned with relevant recruitment literature. Furthermore, the DSS is designed to allow future adjustment of weights, ensuring adaptability across different recruitment contexts. This approach ensures that while expert judgment informs the weighting process, the DSS does not

enforce fixed priorities and can be recalibrated to support different policy contexts. The criteria and weights for workforce recruitment are detailed in Table 2.

Table 2. Criteria And Weights

Criteria			
Code	Name	Type	Weights
1	Education[18]	B	25
2	Work Experience (Duration)[19]	B	30
3	English Skill[18]	B	15
4	Age[20]	C	10
5	Work Experience (Relevance)[19]	B	20
Total			100

The selection of criteria presented in Table 2 is based on relevant recruitment and human resource management literature. Education level and English proficiency are included due to their significant influence on workforce quality and competency development [18]. Work experience is represented through both duration and relevance to capture not only the length of professional exposure but also its alignment with job requirements [19]. The age criterion is incorporated as a cost criterion, reflecting its role in assessing readiness and adaptability in the workplace. Together, these criteria provide a balanced and structured basis for quantitative evaluation using the SAW method [20].

The criterion type indicates how each alternative is evaluated within the SAW framework. Benefit (B) criteria represent attributes where higher values indicate better performance, whereas cost (C) criteria represent attributes where lower values are preferred. To operationalize these criteria for quantitative processing, each main criterion was decomposed into sub-criteria that map qualitative assessments into numerical scores [21]. The sub-criteria scoring scheme defines discrete performance levels for education, work experience duration, English proficiency, and work experience relevance, enabling consistent transformation into normalized values during SAW computation. The age criterion is treated as a cost criterion and is directly entered as a numerical value. The detailed sub-criteria definitions and scoring schemes are presented in Tables 3–7. This

structured sub-criteria design ensures consistency and reduces subjectivity in the evaluation of candidate attributes.

Table 3. Sub-Criteria of Education

C1 = Education (benefit)		
Sub Criteria Name	Description	Assigned Weight
SMA/SMK	Poor	10
Diploma 3	Fair Good	50
S1	Very Good	90

Table 4. Sub-Criteria of Work Experience (Duration)

C2 = Sub-Criteria of Work Experience (benefit)		
Sub Criteria Name	Description	Assigned Weight
Not Experienced	Poor	10
Experienced <2 Years	Fair Good	50
Experienced >2 Years	Very Good	90

Table 5. Sub-Criteria of English Skill

C3 = Sub-Criteria of English Skill (benefit)		
Sub Criteria Name	Description	Assigned Weight
Entry Level	Poor	10
Intermediate Level	Fair Good	50
Advanced Level	Very Good	90

Table 6. Age

C4 = Age (cost)	
Direct Input	

Table 7. Sub-Criteria of Work Experience (Relevance)

C5 = Sub-Criteria of Work Experience (Relevance)	
Sub Criteria Name	Assigned Weight
Poor	10
Fairly Poor	30

C5 = Sub-Criteria of Work Experience (Relevance)	
Sub Criteria Name	Assigned Weight
Fairly Good	50
Good	70
Very Good	90

In the SAW method within DSS, an alternative represents a candidate evaluated and compared to identify the most appropriate recruitment decision. Each alternative is assessed against predefined criteria, where its values are normalized and weighted to generate a final preference score that reflects overall suitability. Alternatives therefore constitute the core elements of the SAW analysis, as the weighting, aggregation, and ranking processes are performed across these entities [22]. The simulated alternatives used for workforce recruitment in this study are presented in Tables 8 and 9.

Table 8. The simulation of alternative for workforce recruitment

No	Alternative	Criteria				
		1	2	3	4	5
1	Andine	SMA/SMK	Not Experienced	Entry Level	24	Fairly Good
2	Louise	Diploma 3	Experienced <2 Years	Intermediate Level	24	Good
3	Urfani	Diploma 3	Experienced <2 Years	Intermediate Level	25	Good
4	Daniel	S1	Experienced <2 Years	Advanced Level	26	Very Good
5	Fransisca	Diploma 3	Experienced <2 Years	Intermediate Level	25	Good
6	Albert	SMA/SMK	Experienced <2 Years	Entry Level	22	Fairly Poor
7	Nael	S1	Experienced >2 Years	Advanced Level	26	Fairly Good
8	Sesil	Diploma 3	Experienced <2 Years	Entry Level	28	Good
9	Salsa	S1	Experienced >2 Years	Intermediate Level	25	Very Good
10	Suzan	S1	Experienced <2 Years	Advanced Level	26	Good

Table 9. The simulation of alternative for workforce recruitment (With Weight)

No	Alternative	Criteria				
		1	2	3	4	5
1	Andine	10	10	10	24	50
2	Louise	50	50	50	24	70
3	Urfani	50	50	50	25	70

No	Alternative	Criteria				
		1	2	3	4	5
4	Daniel	90	90	90	26	90
5	Fransisca	50	90	50	25	70
6	Albert	10	50	10	22	30
7	Nael	90	90	90	26	50
8	Sesil	50	50	10	28	70
9	Salsa	90	90	50	25	90
10	Suzan	90	50	90	26	70

2.3 Usability Scale Test

The usability of the developed Decision Support System (DSS) was evaluated using the System Usability Scale (SUS), a standardized questionnaire introduced by Brooke. SUS consists of ten statements rated on a five-point Likert scale and is widely used to assess perceived usability, ease of use, and overall user satisfaction. Due to its simplicity, reliability, and validity, SUS is commonly applied as a complementary evaluation method alongside technical system testing [23], [24].

In this study, SUS is employed to assess user acceptance and practical feasibility of the proposed DSS rather than to measure technical performance. The interpretation of SUS scores follows established benchmarks, where higher scores indicate better usability and user satisfaction. The SUS score distribution and interpretation framework used in this study are illustrated in Figure 3. Overall, this visualization facilitates a clearer interpretation of SUS results by integrating numerical scores with grading categories, acceptability thresholds, and qualitative assessments of users' subjective experience [25].

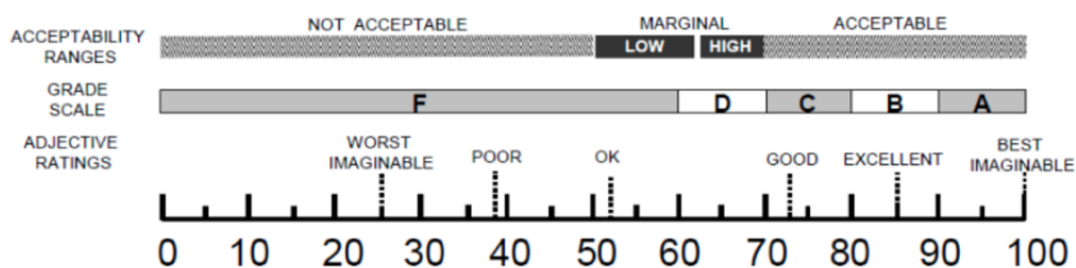


Figure 3. Grade of SUS Results

The usability testing involved 25 participants selected to represent the four primary user roles of the system. The respondents consisted of 10 prospective workers, 10 representatives from participating companies, 3 human resources (HR) professionals, and 2 system administrators. This diverse participant composition ensured that usability feedback reflected multiple user perspectives and provided a comprehensive assessment of the system's practical use.

3. RESULTS AND DISCUSSION

3.1 Data Processing Using SAW Method

This subsection presents the results of data processing using the Simple Additive Weighting (SAW) method and focuses on interpreting how weighted criteria influence the final candidate rankings. This analysis emphasizes the outcome of the normalization and aggregation processes and their implications for recruitment decision-making. The normalization stage requires identifying the maximum and minimum values for each criterion to ensure comparability across different measurement scales. As summarized in Table 10, benefit criteria apply maximum values, while the cost criterion (age) applies the minimum value. This distinction ensures that higher normalized values consistently represent more favorable candidate performance regardless of the criterion type.

Table 10. Identification of maximum and minimum Criterion Values for Normalization

Criteria Code	Criteria type	Maximum Weights	Minimum Weights
1	B	90	
2	B	90	
3	B	90	
4	C		22
5	B	90	

Based on these reference values in Table 10, the decision matrix was normalized using Equation (1). The normalization process transforms the original criterion values into dimensionless scores, as illustrated in Table 11. This step prevents any single criterion from dominating the evaluation solely due to scale differences and enables a fair comparison among candidates.

Table 11. Normalized Criterion Values

No	Alternative	Criteria				
		1	2	3	4	5
1	Andine	0.111	0.111	0.111	0.917	0.556
2	Louise	0.556	0.556	0.556	0.917	0.778
3	Urfani	0.556	0.556	0.556	0.880	0.778
4	Daniel	1.000	1.000	1.000	0.846	1.000
5	Fransisca	0.556	1.000	0.556	0.880	0.778
6	Albert	0.111	0.556	0.111	1.000	0.333
7	Nael	1.000	1.000	1.000	0.846	0.556
8	Sesil	0.556	0.556	0.111	0.786	0.778
9	Salsa	1.000	1.000	0.556	0.880	1.000
10	Suzan	1.000	0.556	1.000	0.846	0.778

After normalization, each criterion value was weighted according to its relative importance and aggregated to obtain the final preference score for each candidate. Higher final scores indicate greater overall suitability for the recruitment decision. The resulting scores and rankings are summarized in Table 12.

Table 12. Final SAW Scores and Candidate Ranking

No	Alternative	Final Score	Ranking
1	Andine	28.056	10
2	Louise	63.611	6
3	Urfani	63.244	7
4	Daniel	98.462	1
5	Fransisca	76.578	5
6	Albert	37.778	9
7	Nael	89.573	3
8	Sesil	55.635	8
9	Salsa	92.140	2
10	Suzan	80.684	4

The ranking results show that Alternative 4 (Daniel) achieved the highest score (98.462), followed by Alternative 9 (Salsa) and Alternative 7 (Nael). Daniel's top ranking is primarily attributed to consistently high performance across all benefit criteria—education level, work experience duration, English proficiency, and work experience relevance—combined with a competitive age value. Since education and work experience duration carry the highest weights in the model, strong performance on these criteria significantly contributes to the final score. This result demonstrates how the SAW method systematically translates weighted criteria into transparent and traceable recruitment outcomes. The results confirm that the SAW-based DSS produces a clear, objective, and interpretable ranking of candidates by explicitly reflecting the contribution of each evaluation criterion in the final decision.

3.2 System Interface

This subsection presents the system interface of the developed Decision Support System (DSS) and discusses its role in supporting usability, transparency, and traceability in the recruitment process. The landing page, shown in Figure 4, functions as the primary access point for users and is designed to provide clear and intuitive navigation to core system features, including job vacancy information, applicant registration, and system access. By presenting key system functions in a structured and easily understandable manner, the interface facilitates efficient user interaction and supports transparent engagement with the recruitment process. Figure 5 presents the job vacancy interface, which functions as a transparent information layer within the recruitment system. This interface enables prospective applicants to access structured and up-to-date vacancy information, including position details and application timelines, before initiating the registration process. By clearly presenting recruitment opportunities and guiding applicants through a standardized application flow, the interface supports usability and ensures that the initial stage of candidate selection is conducted in an open and traceable manner.

Figure 6 presents the criteria management interface, where evaluation criteria and their corresponding weights are defined by the human resources (HR) department. This interface allows authorized users to explicitly determine which criteria are applied in the recruitment process and to assign relative importance to each criterion. By displaying criterion types (benefit or cost) and their weights in a structured and visible manner, the system enhances transparency in how recruitment decisions are formulated.

Furthermore, the explicit presentation of criteria and weights ensures traceability, as the contribution of each criterion to the final candidate ranking can be directly examined and justified within the SAW-based decision-making process.



Figure 4. Landing Page

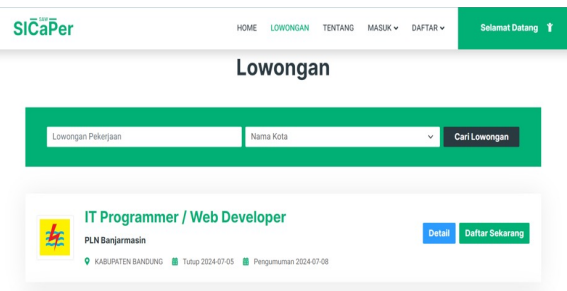


Figure 5. job vacancies currently offered

+ Kembali

Berikut daftar nama calon pekerja berdasarkan Rangkang dari Perhitungan Metode SAW
 Status Kelolosan Pada Lowongan ini akan ditampilkan pada calon pekerja pada : 1 Agustus 2024

Lowongan yang Anda buat akan ditampilkan pada calon pekerja jika kriteria sudah dibuat !

Data Kriteria

Data kriteria dari lowongan yang dipilih

ID	Nama Kriteria	Tipe Kriteria	Bobot	Cara Penilaian	Actions
33	Pendidikan	benefit	25	Pilihan Sub Kriteria	Edit Hapus
35	Pengalaman	benefit	30	Pilihan Sub Kriteria	Edit Hapus
36	Bahasa Inggris	benefit	15	Pilihan Sub Kriteria	Edit Hapus
37	Umur	cost	10	Input Langsung	Edit Hapus
38	Penguasaan Bahasa Pemrograman Web	benefit	20	Pilihan Sub Kriteria	Edit Hapus
Jumlah Bobot (Pastikan Bobot Berjumlah 100)			100	Bobot terpenuhi 100	

+ Tambah Kriteria

Figure 6. Criteria Data

+ Kembali

Berikut daftar nama calon pekerja berdasarkan Rangkang dari Perhitungan Metode SAW
 Status Kelolosan Pada Lowongan ini akan ditampilkan pada calon pekerja pada : 1 Agustus 2024

Lowongan yang Anda buat akan ditampilkan pada calon pekerja jika kriteria sudah dibuat !

Perbarui Hasil **Status Kelolosan** **Cetak Hasil Kelolosan** **Upload Hasil TTD**

Rangking	Calon Pekerja	Nomor Hp	CV	Status	Hasil SAW	Actions
1	Dayat	083478654322	Lolos	Lolos	98.5	Data Calon Edit Status
2	Nopita	081356778096	Lolos	Lolos	89.7	Data Calon Edit Status
3	Salisa	081245327688	Lolos	Lolos	87.8	Data Calon Edit Status
4	Suzan	081267349832	Lolos	Lolos	80.9	Data Calon Edit Status
5	Fikri	081324567854	Lolos	Lolos	76.8	Data Calon Edit Status
6	Iaras	085645879087	Tidak Lolos	Tidak Lolos	64	Data Calon Edit Status
7	upik	084527889021	Tidak Lolos	Tidak Lolos	63.6	Data Calon Edit Status
8	Sesil	082345667843	Tidak Lolos	Tidak Lolos	55.95	Data Calon Edit Status

Figure 7. list of applicant or alternative

Figure 7 presents the final ranking results generated by the SAW-based Decision Support System, displaying each applicant along with their corresponding final preference score. This interface represents the culmination of the evaluation process, where normalized and weighted criteria are aggregated to produce an objective ranking of candidates. By explicitly presenting final scores and ranking positions, the system enables transparent decision-making and allows recruitment outcomes to be traced back to the predefined criteria and weights. The displayed results support accountable candidate selection by clearly distinguishing between qualified and non-qualified applicants based on systematic evaluation.

3.3 System Using Usability Scale Test Results

This subsection presents the usability evaluation results of the developed Decision Support System (DSS) using the System Usability Scale (SUS). The SUS method was

employed to assess users' perceptions of ease of use, clarity, and overall satisfaction when interacting with the system during the recruitment process. The usability evaluation involved 25 respondents, consisting of job applicants, human resources (HR) personnel, company representatives, and system administrators. The overall SUS results are summarized in Table 13, which presents the aggregated usability indicators rather than individual respondent scores.

Table 13. System Usability Scale Evaluation

Indicator	Value
Number of respondents	25
Average SUS score	87.6
SUS grade	A
Acceptability range	Excellent
Adjective rating	Best Imaginable

Based on established SUS interpretation benchmarks, an average score of 87.6 corresponds to an "A" grade, falls within the "Excellent" acceptability range, and is categorized as "Best Imaginable" in terms of adjective ratings. These results suggest that users found the system intuitive, easy to learn, and suitable for supporting recruitment-related tasks. It should be noted that a small number of respondents produced individual SUS scores exceeding 100. This phenomenon occurs due to the standard SUS scoring conversion process, where consistently positive responses across all questionnaire items can result in scores slightly above the conventional upper bound. Such values do not indicate measurement errors and do not affect the overall interpretation of system usability, as SUS evaluations are primarily assessed based on average scores and categorical interpretations rather than individual extreme values. Overall, the SUS evaluation confirms that the developed DSS demonstrates high usability and is acceptable for practical implementation in supporting transparent and efficient recruitment decision-making.

3.4 Discussion

The findings of this study indicate that the developed Decision Support System (DSS) is able to strengthen recruitment decision-making by shifting the evaluation process from largely intuitive judgment toward a structured, criteria-based assessment. Importantly,

the value of the system is not primarily in computational sophistication, but in how the Simple Additive Weighting (SAW) mechanism operationalizes recruitment criteria into a transparent and repeatable ranking process. By converting diverse applicant attributes into normalized scores and aggregating them using explicitly assigned weights, the DSS produces outcomes that are consistent, interpretable, and easier to justify than conventional manual screening. This directly addresses the problem identified in the introduction: recruitment practices in local contexts (such as Banjarmasin) often remain conventional and difficult to audit despite broader Smart City readiness.

A key contribution of the results lies in demonstrating how weighting structures shape recruitment outcomes in an accountable way. The ranking results show that Daniel achieved the highest preference score (98.462), followed by Salsa (92.140) and Nael (89.573). These outcomes are coherent with the weighting scheme in Table 2, where Work Experience (Duration) (30) and Education (25) carry the greatest influence, followed by Work Experience (Relevance) (20) and English Skill (15). Because Daniel scored highly across the major benefit criteria—education, experience duration, English proficiency, and relevance—his final score remained dominant even with age treated as a cost criterion. In practice, this demonstrates a crucial governance advantage: decision-makers can explain why a candidate ranks higher by tracing the contribution of each criterion through normalization (Table 11) and weighted aggregation (Equation 2). Rather than presenting a ranking as a “black-box” output, the model enables decision logic to be articulated in a form that aligns with algorithmic transparency expectations in Smart Governance settings.

From a Smart Governance perspective, the study shows that the DSS supports accountability through traceability and visibility of decision parameters. The interface design plays an enabling role here. The criteria management page (Figure 6) explicitly displays the applied criteria, their types (benefit/cost), and weights, making the evaluative structure visible to authorized stakeholders. Likewise, the final ranking interface (Figure 7) presents preference scores and ranking positions in a clear format that can be reviewed and documented. This matters because accountability in public-sector recruitment is not only about producing a ranking, but about ensuring that the ranking can be audited, defended, and revisited if contested. In other words, the SAW method becomes more than a scoring technique—it functions as a governance tool that supports

decision traceability and institutional legitimacy, which is a gap identified in prior recruitment DSS studies that focus mainly on efficiency rather than governance outcomes.

The usability findings further strengthen the case for practical adoption. The SUS average score of 87.6—categorized as Grade A, “Excellent,” and “Best Imaginable”—suggests that the system is likely to be accepted across user groups with different roles and technical familiarity. This point is particularly important in municipal contexts, where recruitment workflows involve diverse stakeholders (HR staff, administrators, applicants, and external partners). A technically transparent system that is difficult to use would fail in practice; conversely, a usable system that hides decision logic would fail governance expectations. Here, the combined evidence from the interface design and the SUS outcome indicates that the DSS balances these demands: it is understandable to users while still exposing key decision parameters in ways that support oversight. While a small number of individual SUS scores exceeded 100 due to scoring conversion effects, this does not undermine the overall interpretation, since SUS is most reliably interpreted via mean score and benchmark categories rather than isolated extremes.

The policy implications for local government human resource management are significant, particularly in the context of Banjarmasin’s Smart City ambitions. By formalizing recruitment criteria, documenting weights, and producing auditable preference scores, the DSS provides a practical pathway for aligning recruitment processes with Smart Governance principles of transparency, accountability, and evidence-based decision-making. In public administration, recruitment decisions affect institutional capability and public trust; therefore, improving the visibility and defensibility of hiring outcomes can reduce perceptions of favoritism and strengthen legitimacy. The DSS also supports standardization across hiring cycles by preserving criteria definitions and providing consistent evaluation procedures—an important step toward reducing fragmentation often associated with manual or semi-structured recruitment practices.

At the same time, the results should be interpreted with an awareness of governance risks and methodological limitations. First, while the DSS reduces unstructured subjectivity, it does not eliminate embedded subjectivity—particularly in the selection of

criteria, the discretization of qualitative attributes into sub-criteria weights (Tables 3–7), and the expert-driven assignment of criterion weights (Table 2). These design choices can introduce bias if not periodically reviewed or if they reflect narrow organizational preferences that disadvantage certain groups. Second, the current implementation relies on simulated alternatives, which is useful for demonstrating method performance but may not capture the complexity, variance, and missing-data issues typical in real recruitment datasets. Third, the use of age as a cost criterion raises governance and ethical considerations in some contexts; even where legally permissible, age-related evaluation requires careful justification, clear policy grounding, and safeguards to prevent discriminatory outcomes. For Smart Governance alignment, transparency must be paired with fairness checks, not treated as a substitute for them.

Accordingly, this study supports positioning the DSS as a decision-support tool rather than a fully automated decision authority. Human oversight remains essential to interpret results, validate data accuracy, and incorporate contextual considerations that may not be captured by quantitative criteria. To strengthen future implementation, several enhancements are recommended: (1) sensitivity analysis to examine how changes in weights affect rankings and to detect over-dominance of particular criteria; (2) periodic stakeholder review of criteria and sub-criteria scoring to reduce embedded bias and ensure relevance to evolving job requirements; (3) improved audit logging to document who changes weights and when; and (4) integration of fairness and compliance checks consistent with public-sector recruitment regulations. These steps would deepen the system's contribution to Smart Governance by ensuring that transparency and usability are accompanied by robust procedural safeguards.

4. CONCLUSION

This study achieved its objective of strengthening transparency, objectivity, and accountability in recruitment within a Smart City governance context by designing and implementing a Decision Support System (DSS) using the Simple Additive Weighting (SAW) method. The results show that the system can systematically convert both qualitative and quantitative applicant attributes into normalized, weighted values that produce a clear and traceable ranking. The SAW computation generated consistent and interpretable outcomes, with the top-ranked candidate obtaining a final preference score

of 98.462. This demonstrates that the proposed approach can reduce reliance on unstructured subjective judgment by embedding recruitment decisions in an explicit, criteria-based evaluation model. From the perspective of usability and operational feasibility, the DSS achieved an average System Usability Scale (SUS) score of 87.6, which falls in the “Excellent” acceptability range and corresponds to Grade A. This indicates that users across different roles—applicants, HR personnel, and system administrators—perceived the system as intuitive and easy to learn. High usability is particularly important in public-sector environments, where systems must support consistent implementation, minimize training burden, and encourage routine use across stakeholders with varying levels of technical expertise. The SUS result therefore provides practical evidence that the system is not only methodologically sound but also ready for organizational adoption.

In practical and governance terms, the DSS functions as a governance-support instrument rather than merely a technical recruitment tool. By explicitly presenting evaluation criteria, criterion types (benefit/cost), assigned weights, and final preference scores, the system enables recruitment decisions to be audited and justified. This traceability aligns with Smart City governance principles that emphasize accountable and data-driven public administration. For municipal human resource management, the proposed framework offers a structured approach to recruitment that can help standardize assessments, reduce the risk of bias arising from inconsistent judgment, and strengthen public trust by making decision logic more transparent. At the same time, the DSS is positioned as a decision-support mechanism, ensuring that final hiring authority remains under human oversight while benefiting from systematic analysis.

Future research can expand this work by deploying the DSS in larger recruitment settings across multiple institutions or regions to evaluate scalability, performance stability, and generalizability in real operational contexts. Further studies may also test alternative or hybrid multi-criteria decision-making approaches to compare ranking robustness and sensitivity to criteria weighting, particularly where policy priorities shift across job types. In addition, integrating the DSS with broader e-government or Smart City platforms could support end-to-end digital recruitment governance, enabling more comprehensive audit trails, interoperability with administrative systems, and stronger alignment between recruitment practices and policy-driven public-sector transformation.

REFERENCES

- [1] E. Knies, P. Boselie, J. Gould-Williams, and W. Vandenabeele, "Strategic human resource management and public sector performance: Context matters," *Int. J. Hum. Resour. Manag.*, vol. 28, no. 24, pp. 5192–5213, 2017, doi: 10.1080/09585192.2017.1407088.
- [2] B. Z. Poljašević, A. M. Gricnik, and S. Š. Žižek, "Human resource management in public administration: The ongoing tension between reform requirements and resistance to change," *Adm. Sci.*, vol. 15, no. 3, p. 94, 2025, doi: 10.3390/admsci15030094.
- [3] H. Konateh, E. K. Duramany-Lakkoh, and E. Udeh, "Cost and administrative effectiveness of recruitment and selection practices on public service delivery in public sector institutions," *Eur. J. Bus. Manag. Res.*, vol. 8, no. 2, pp. 21–30, 2023.
- [4] M. T. P. Lubis, U. T. Handayani, N. T. Aganta, R. F. Dalimunthe, and P. Lumbanraja, "Analysis of civil servant recruitment in Indonesia: Challenges and opportunities in the digital era (Analisis rekrutmen pegawai negeri sipil di Indonesia: Tantangan dan peluang di era digital)," *Int. J. Econ. Manag. Sci.*, vol. 1, no. 4, pp. 446–454, 2024, doi: 10.61132/ijems.v1i4.399.
- [5] B. Baykurt, "Algorithmic accountability in U.S. cities: Transparency, impact, and political economy," *Big Data Soc.*, vol. 9, no. 2, 2022, doi: 10.1177/20539517221115426.
- [6] H. Taherdoost, "Analysis of simple additive weighting method (SAW) as a multi-attribute decision-making technique: A step-by-step guide," *J. Manag. Sci. Eng. Res.*, vol. 6, no. 1, pp. 21–24, 2023, doi: 10.30564/jmser.v6i1.5400.
- [7] N. Vafaei, R. A. Ribeiro, and L. M. Camarinha-Matos, "Assessing normalization techniques for simple additive weighting method," *Procedia Comput. Sci.*, vol. 199, pp. 1229–1236, 2021, doi: 10.1016/j.procs.2022.01.156.
- [8] D. Pibriana, "Application of the simple additive weighting (SAW) method in employee recruitment decision-making at PT. ABC (Penggunaan metode simple additive weighting (SAW) dalam pengambilan keputusan rekrutmen karyawan pada PT. ABC)," *Techno.Com*, vol. 19, no. 1, pp. 45–55, 2020, doi: 10.33633/tc.v19i1.2771.
- [9] R. A. Saputri, A. N. Sianturi, S. Mutmainnah, and E. R. Yulia, "Decision support system for new employee recruitment using the simple additive weighting (SAW) method at PT Crestec Indonesia Cikarang (Sistem penunjang keputusan penerimaan karyawan baru menggunakan metode simple additive weighting (SAW) pada PT

- Crestec Indonesia Cikarang)," *JIKO (J. Inform. dan Komput.)*, vol. 6, no. 2, p. 207, 2022, doi: 10.26798/jiko.v6i2.627.
- [10] M. Saputra and L. Bachtiar, "Analysis of employee recruitment at PT. Srikandi Diamond Indah Motors Sampit using the analytical hierarchy process (AHP) and simple additive weighting (SAW) methods (Analisis penerimaan karyawan pada PT. Srikandi Diamond Indah Motors Sampit dengan metode analytical hierarchy process (AHP) dan simple additive weighting (SAW))," *J. Sisfokom (Sist. Inf. dan Komput.)*, vol. 10, no. 3, pp. 312–319, 2021, doi: 10.32736/sisfokom.v10i3.1239.
- [11] L. Mazia, L. A. Utami, M. B. Himawan, A. D. Lestari, and M. Aprilia, "Decision support system for employee recruitment using the simple additive weighting (SAW) method at PT. Ponny Ekspres Suksestama Jakarta (Sistem pendukung keputusan penerimaan karyawan menggunakan metode simple additive weighting (SAW) pada PT. Ponny Ekspres Suksestama Jakarta)," *IJIS (Indones. J. Inf. Syst.)*, vol. 6, no. 1, p. 1, 2021, doi: 10.36549/ijis.v6i1.122.
- [12] S. G. Meshram, E. Alvandi, C. Meshram, E. Kahya, and A. M. F. Al-Quraishi, "Application of SAW and TOPSIS in prioritizing watersheds," *Water Resour. Manag.*, vol. 34, no. 2, pp. 715–732, 2020, doi: 10.1007/s11269-019-02470-x.
- [13] F. N. Khasanah and H. Herlawati, "Culinary places recommendation system in Bekasi City using the simple additive weighting method," *PIKSEL*, vol. 9, no. 1, pp. 63–74, 2021, doi: 10.33558/piksel.v9i1.2621.
- [14] A. Sadeghi, A. Maleki, M. H. Ahmadi, and A. H. Kiani, "Comparative evaluation of renewable energy investments: A multi-criteria decision-making approach," *Energy Convers. Manag. X*, vol. 28, 2025, doi: 10.1016/j.ecmx.2025.101190.
- [15] M. Grdinić-Rakonjac and M. Lučić, "Electric vehicle selection with easy applicable MCDM methods," *Transp. Res. Procedia*, vol. 82, pp. 782–789, 2025, doi: 10.1016/j.trpro.2025.06.079.
- [16] H. Aljaghoub *et al.*, "Comparative analysis of various oxygen production techniques using multi-criteria decision-making methods," *Int. J. Thermofluids*, vol. 17, 2023, doi: 10.1016/j.ijft.2022.100261.
- [17] M. R. T. Kurnia, E. P. W. Mandala, and R. Prawiro, "Decision support system for loan eligibility using the simple additive weighting (SAW) method," *J. Comput. Sci. Inf. Technol.*, vol. 9, no. 4, pp. 176–180, 2023, doi: 10.35134/jcsitech.v9i4.84.

- [18] M. L. M. Cahigas, R. C. A. Robielos, and M. J. J. Gumasing, "Application of multiple criteria decision-making methods in the human resource recruitment process," [details unavailable].
- [19] P. Ziemba, "Comparison of multi-criteria decision aiding methods in the problem of employee recruitment," *Procedia Comput. Sci.*, vol. 225, pp. 2704–2713, 2023, doi: 10.1016/j.procs.2023.10.262.
- [20] P. Sarangi, R. Mishra, and A. Padhi, "Balancing skills and expectations: AHP analysis of competency-based recruitment in the EdTech sector," *Future Bus. J.*, vol. 11, no. 1, 2025, doi: 10.1186/s43093-025-00483-0.
- [21] G. Rinaldi, K. Theodorakos, F. Crema Garcia, O. M. Agudelo, and B. De Moor, "DSS4EX: A decision support system framework to explore artificial intelligence pipelines with an application in time series forecasting," *Expert Syst. Appl.*, vol. 269, 2025, doi: 10.1016/j.eswa.2025.126421.
- [22] T. Singh, P. Pattnaik, S. R. Kumar, G. Fekete, G. Dogossy, and L. Lendvai, "Optimization on physicomaterial and wear properties of wood waste filled poly(lactic acid) biocomposites using integrated entropy-simple additive weighting approach," *S. Afr. J. Chem. Eng.*, vol. 41, pp. 193–202, 2022, doi: 10.1016/j.sajce.2022.06.008.
- [23] M. Gao, P. Kortum, and F. L. Oswald, "Multi-language toolkit for the system usability scale," *Int. J. Hum.-Comput. Interact.*, vol. 36, no. 20, pp. 1883–1901, 2020, doi: 10.1080/10447318.2020.1801173.
- [24] A. M. Deshmukh and R. Chalmata, "Validation of system usability scale as a usability metric to evaluate voice user interfaces," *PeerJ Comput. Sci.*, vol. 10, 2024, doi: 10.7717/peerj-cs.1918.
- [25] R. M. A. Putri, W. G. S. Parwita, I. P. S. Handika, I. G. I. Sudipa, and P. P. Santika, "Evaluation of accounting information system using usability testing method and system usability scale," *Sinkron*, vol. 9, no. 1, pp. 32–43, 2024, doi: 10.33395/sinkron.v9i1.13129.