

## Aggregation Model to Determine Criteria Weights for Integrated Primary Health Care Information System (IPCIS) Implementation

Sri Kusumadewi<sup>\*1</sup>, Rahadian Kurniawan<sup>2</sup>, Elyza Gustru Wahyuni<sup>3</sup>, Aridhanyati Arifin<sup>4</sup>, Linda Rosita<sup>5</sup>, Mutmainna<sup>6</sup>

<sup>1,2,3,4,6</sup>Informatics Department, Universitas Islam Indonesia, Yogyakarta, Indonesia

<sup>5</sup>Faculty of Medicine, Universitas Islam Indonesia, Yogyakarta, Indonesia

Email: <sup>1</sup>sri.kusumadewi@uui.ac.id

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### Abstract

Implementation of the Integrated Primary Health Care Information System (IPCIS) in integrated community health posts (posyandu) is influenced by various factors, including technical aspects, human resources, policies, and data governance. Given the diverse field conditions, the impact of each factor can vary, so it is important to understand the relative importance of each criterion. This study aims to determine the weight of the criteria that influence the implementation of IPCIS in posyandu. Ten people answered the questions correctly (out of 22 respondents), including cadres, sub-district staff, and health workers from Tirtorahayu Village. Respondent preferences were collected using three approaches: rank-based aggregation (Borda, Condorcet, Copeland), score-based aggregation (average), and voting-based aggregation (plurality and majority) to obtain the criteria weights ( $w$ ) and a comparative analysis between the approaches. The findings demonstrate that the IPCIS criteria for security and protection of personal data were consistently given the highest weights. In the ranking-based aggregation approaches ( $w_{\text{Borda}}=0.11$ ,  $w_{\text{Condorcet}}=0.20$ ,  $w_{\text{Copeland}}=0.19$ ). In score-based aggregation approaches ( $w=0.11$ ). In voting-based aggregation approaches ( $w=0.15$ ). It is indicating a strong group consensus regarding the importance of these aspects in IPCIS implementation. The combination of ranking-based and score-based aggregation resulted in stable IPCIS implementation criterion weights that reflected group consensus, with voting-based aggregation acting as validation. The practical implication is that the obtained weighted criteria can be used as a basis for determining program priorities and resource allocation when implementing IPCIS.

**Keywords :** *Criteria's Weighting, Integrated Primary Care Information System, Posyandu, Rank-Based Aggregation, Score-Based Aggregation, Voting-Based Aggregation.*

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## 1. INTRODUCTION

Primary care serves as the entry point to healthcare and aims to integrate and coordinate the many facets of a patient's health and treatment in a comprehensive manner [1]. In low- and middle-income nations, strengthening primary health care is the most economical way to attain long-term universal health coverage, guard against health shocks, and enhance everyone's health and well-being [2], [3]. Consequently, the Integrated Primary Care Information System (IPCIS), is crucial [4], [5]. Approximately 10,260 community health centers in Indonesia provide primary healthcare services [6]. These services also include recording and reporting health data, either using a digital Health Information System (HIS) or manual reporting. Utilizing HIS is crucial for capturing the dynamic evolution of health problems and monitoring interventions; thus, it provides effective primary healthcare services to the community [7].

There are several factors that influence the implementation of the IPCIS. These factors include technical aspects, human resources, policies, and data governance, all of which play a role in supporting the sustainability of the health information system. The extent to which each of these factors can function

optimally and support each other largely determines the success of this system. The contribution of each component is not necessarily equally strong in practice due to differences in field circumstances.. For example, in one region, the biggest bottleneck may lie in digital infrastructure, while in another it is more related to human resource capacity. This creates a need to understand the relative importance of each influential criterion. In this way, the implementation strategy can be focused on the factors that have the greatest influence on the success of implementing IPCIS in posyandu.

Currently, there is not much research on IPHS. More research is focused on HIS implemented in community health centers. According to a study [6], community health centers use 91.54% of HIS, which is in line with their requirements, and 90% of the data gathered has been consulted when making decisions, developing health policies, or creating new programs. However, there are drawbacks to using the current HIS. For example, 49% of Indonesia's HIS contain too many data input factors, which results in lengthy form filling, longer wait times for patient registration, and more screen time for medical staff. Furthermore, 29% of HIS are unable to do automated data analysis, 21% of HIS are not user-friendly, and 33% of the systems frequently face outages, which makes it difficult to manage data and provide health services.

Although there are not many studies that specifically discuss the factors determining the success of IPCIS implementation, several studies on service integration at the primary care level can be used as a reference. One important aspect is the ability of cadres and health workers to operate the IPCIS or application. The digital capacity of cadres, built through training, is vital to ensuring they can run the digital health system effectively [8], [9], [10]. A survey [6], showed that 74.30% of personnel at community health centers only received training during the initial system installation, 13.64% indicated that instruction occurred only once a year, and 10.30% reported no training for data input and management. Instruction.

The posyandu must have equipment and a strong internet connection to keep this system going. Based on a survey [6], 9.45% of community health centers do not have internet access. Unequal access to digital infrastructure risks widening health disparities, especially in the use of telemedicine-based services [11]. Therefore, to ensure health workers can run the application without obstacles, we need an equitable strategy and consistent technical support [12], [13], [14]. In this context, data governance also plays an important role. Accurate, complete, and regularly updated data is the basis for making the right decisions.[15].

The integration of IPCIS with national and regional platforms such as SatuSehat and P-Care is also quite an important factor. This kind of integration not only enables cross-system data exchange but also supports the concept of a learning health system that is oriented towards continuous improvement in service quality [16]. A user-friendly interface is equally important because a simple and easy-to-understand user interface can increase user comfort [17], [18], [19]. The presence of a health dashboard that can be accessed by community health centers and village officer will also help monitor community conditions in real-time so that interventions can be carried out more quickly [20].

On the other hand, policy support from the national and regional levels determines the direction of the use of health information systems. Clear and measurable policies can encourage the creation of effective information exchange and strengthen the digital ecosystem in the health sector [21], [22]. We must also acknowledge the significance of policy and governance frameworks, which encompass API usage platforms, blockchain, and interoperability frameworks. This type of policy approach is the foundation for creating a health data ecosystem that is open, transparent, and accessible in real time [23], [24]. Furthermore, aspects of security and personal data protection also require serious attention. The use of technologies such as IoT, blockchain, mobile health applications, and cloud computing can be solutions to ensure the security and maintain the confidentiality of medical data [25]. By considering all

these factors comprehensively, the implementation of IPCIS is expected to run optimally and sustainably.

Today, no study has systematically assessed the relative importance of each factor. Therefore, an approach is needed to help quantify and prioritize the most influential criteria for IPCIS implementation at posyandu. This study aims to determine the weights of the criteria that influence IPCIS implementation at posyandu. The opinions of community health volunteers are crucial because they are the frontline users who understand the field workflow, real-world conditions in the community, and operational constraints in IPCIS implementation. Considering community health volunteers' input will improve the system's suitability to the local context, strengthen ownership, and encourage adoption and sustainability. The weighting was done by a group of community health volunteers, so the results show what the group as a whole thinks, not what each person thinks. Thus, the weights obtained can illustrate the relative importance of each criterion in the context of IPCIS implementation.

This study has three main contributions. First, it provides a systematic analytical framework for determining the weighting of criteria influencing IPCIS implementation in posyandu. Second, through a participatory approach involving decision-making groups, this study produces weightings that reflect not only individual perceptions but also a more representative collective consensus. Third, the results of this study can serve as a basis for policymakers and healthcare managers in setting strategic priorities, optimizing resource allocation, and guiding the development of health information systems to meet real-world needs. By addressing challenges and leveraging proven strategies, countries can move closer to achieving the goal of universal health coverage and improving health outcomes for all [26].

## 2. METHOD

This research will be conducted in five main steps: developing a questionnaire, collecting preference data, aggregating preferences, analyzing data, and developing recommendations. The research flow can be seen in Figure 1.

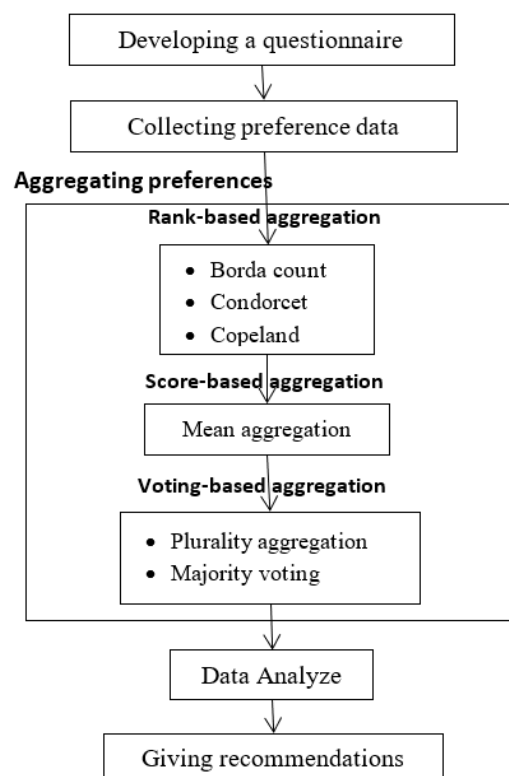


Figure 1. Research Stages

## 2.1. Developing A Questionnaire

This study used a questionnaire as a data collection instrument. The data collected in the questionnaire included respondents' demographics and preferences. Preferences represent respondents' assessments of the criteria or factors that need to be considered in implementing IPCIS at posyandu. Demographic data included gender, age, and education. We provided 10 criteria, as shown in Table 1. These criteria were determined based on relevant references.

Table 1. Decision Making Criteria

Code	Criteria	Reference
C1	The ability of cadres and health workers to use IPCIS	[8], [9], [10]
C2	Availability of devices and internet networks at posyandu	[11]
C3	Ongoing training for cadres and health workers on information systems	[8], [9], [10]
C4	Data governance: accuracy, completeness, and regular data updates	[15]
C5	Integration of the IPCIS with other systems (Satu Sehat or P-Care)	[16]
C6	User-friendly user interface	[17], [18], [19]
C7	A dashboard accessible to Community Health Centers and Village Officers for monitoring	[20]
C8	National/regional policies that encourage and direct the use of information systems	[21], [22]
C9	Technical support in case of problems (troubleshooting, hotlines, etc.)	[12], [13], [14]
C10	Protection of personal data and security of health information systems	[25]

Respondents were asked to rank each criterion as a priority. A lower number (1) indicates the highest priority factor, while a higher number (10) indicates the lowest priority factor. Respondents were allowed to rank multiple criteria the same way. We used Google Forms to distribute the questionnaire.

## 2.2. Collecting Preference Data

Respondents in this study consisted of volunteers or cadres, village staff, and health workers from Tirtorahayu Village, DIY Province, Indonesia. A total of 22 respondents participated in completing a prepared questionnaire. Tirtorahayu Village was selected as the research location due to its proven success in implementing the posyandu information system [27], [28]. All respondents involved were confirmed to have experience using the Posyandu information system, ensuring the data obtained was relevant to the research objectives.

After the data collection process was completed, the next stage was validity testing to ensure data quality. At this stage, data identified as outliers were removed to prevent them from affecting the analysis results. Only valid data that met the criteria were used in the subsequent process, ensuring more accurate and reliable research findings.

## 2.3. Aggregating Preferences

We processed each respondent's ranking results. The ranking results were then aggregated to obtain a final score. The number of volunteers in this study was substantial, and individual preferences could be utilized without the need for negotiation or consensus. Therefore, the aggregation method was preferred over consensus. We conducted aggregation using three approaches: rank-based aggregation, score-based aggregation, and voting-based aggregation. Rank-based aggregation used three methods: Borda Count, Condorcet, and Copeland. Score-based aggregation used the mean method. Voting-based aggregation used two methods: plurality aggregation and majority voting.

To rank criteria using the Borda rule, decision-makers must first obtain their preference rankings [29]. Suppose there are  $m$  criteria to be selected. If factor  $C_i$  is ranked  $\theta$ -th, the Borda count of  $C_i$  is  $B(C_i) = m - \theta + 1$ , which is the number of factors that are outperformed by  $C_i$ . The factor with the highest Borda count is ranked first, and the factor with the lowest Borda count is ranked last.

The Condorcet Method is a decision-making method that determines the winner based on pairwise comparisons between all alternatives [30], [31]. An alternative is considered a Condorcet winner if it outperforms all other alternatives in a head-to-head comparison. In other words, if A is preferred over B, C, and D in a head-to-head comparison by a majority of decision-makers, then A is the winner. The Condorcet algorithm is shown in Figure 2.

```

1. Input: Ranking matrix  $R_{ij}$ , m: number of decision makers, n: number of criteria
2. Initialize: For each criterion  $C_i$ , set Condorcet score,  $S_i=0$ .
3. Pairwise comparisons:
   For each pair of criteria  $(C_i, C_j), i < j$ :
   a. Set  $T_i=0, T_j=0$ .
   b. For each decision maker k:
      • If  $R_{ki} < R_{kj}$ , then  $T_i=T_i+1$ , else
      • If  $R_{kj} < R_{ki}$ , then  $T_j=T_j+1$ , else
      • If  $R_{ki}=R_{kj}$ , then do nothing
   c. Compare results:
      • If  $T_i > T_j$ , then  $S_i=S_i+1$ 
      • If  $T_j > T_i$ , then  $S_j=S_j+1$ 
      • If  $T_i = T_j$ , then  $S_i=S_i+0.5$  and  $S_j=S_j+0.5$ 
4. Normalization:
   For each i:  $W_i = \frac{S_i}{\sum_{k=1}^n S_k}$ 
5. Ranking:
   Sort criteria by descending  $W_i$ 
6. Output:
   • Condorcet scores of all criteria ( $S_i$ )
   • Normalized weights ( $W_i$ )
   • Final ranking
    
```

Figure 2. Condorcet Algorithm

The Copeland Score is a method used to determine a ranking or winner by comparing alternative [32], similar to the Condorcet method. Each alternative is compared with all other alternatives one by one. If alternative A is preferred by the majority of voters over alternative B, then A wins in the comparison. The final score indicates how dominant an alternative is compared to the others. The Copeland algorithm is shown in Figure 3.

```

1. Input:
   Ranking matrix  $R_{ij}$ , m: number of decision makers, n: number of criteria
2. Initialize:
   For each criterion  $C_i$ , set
   • Copeland score:  $S_i=0$ ,
   • Win Score:  $V_i=0$ ,
   • Lose Score:  $L_i=0$ ,
   • Draw Score:  $D_i=0$ .
3. Pairwise comparisons:
   For each pair of criteria  $(C_i, C_j), i < j$ :
   a. Set  $T_i=0, T_j=0$ .
   b. For each decision maker k:
      • If  $R_{ki} < R_{kj}$ , then  $T_i=T_i+1$ , else
      • If  $R_{kj} < R_{ki}$ , then  $T_j=T_j+1$ , else
      • If  $R_{ki}=R_{kj}$ , then do nothing
   c. Compare results:
      • If  $T_i > T_j$ , then  $V_i=V_i+1, L_j=L_j+1$ 
      • If  $T_j > T_i$ , then  $V_j=V_j+1, L_i=L_i+1$ 
      • If  $T_i = T_j$ , then  $D_i=D_i+0.5$  and  $D_j=D_j+0.5$ 
   d. Copeland score:  $S_i = V_i - L_i + D_i$ 
4. Normalization:
   For each i:  $W_i = \frac{S_i}{\sum_{k=1}^n S_k}$ 
5. Ranking:
   Sort criteria by descending  $W_i$ 
6. Output:
   • Copeland scores of all criteria ( $S_i$ )
   • Normalized weights ( $W_i$ )
    
```

Figure 3. Copeland Algorithm

Because preference data is ranking-based, it requires a conversion process into scores for quantitative processing. This conversion is accomplished by assigning numerical values based on ranking position, with rank 1 given a score of 10, rank 2 a score of 9, and so on, until the last rank has

the lowest score. These converted scores can then be aggregated using the mean ranking aggregation method to produce a collective ranking. Mean ranking involves collecting all the ratings given by respondents for each factor and then calculating the average of these ratings as the aggregate ranking. After calculating the average for each factor, the factors are ranked based on that average, from lowest (highest ranking) to highest [33].

Majority voting will choose the alternative that receives more than 50% of the votes (absolute majority) as the winner. There must be more than half of the voters who agree with one alternative. In Plurality Aggregation, the alternative that receives the most votes (not a majority) is considered the winner, even if it does not reach more than 50% [34]. This method does not require an absolute majority and is suitable for choosing more than two alternatives.

#### 2.4. Calculating Criteria Weights

In the Borda, Copeland, Mean, and Plurality Aggregation methods, the final score obtained for each criterion can be directly normalized into a relative weight. This is done by dividing the score of one criterion by the total score of all criteria. In the Condorcet and Majority Voting methods, the calculation results more often produce a single winner than a weighted distribution. However, the relative weight can still be calculated using the proportion of wins or the proportion of votes to the total. In general, the relative weight for the  $i$ -th criterion ( $C_i$ ) with a score/win of  $S_i$  can be calculated based on Equation (1).

$$W_i = \frac{S_i}{\sum_{k=1}^n S_k} \quad (1)$$

#### 2.5. Data Analysis

Data analysis will be conducted by comparing the results of each method in each approach: rank-based aggregation, score-based aggregation, and voting-based aggregation. Analysis using the rank-based approach focuses on ranking consistency and differences between positions [35]. In rank-based aggregation, analysis is conducted by looking at the consistency of weights against the average ranking, criteria that are always dominant, and differences in criteria weights. The greater the distance in weights between the top and bottom rankings, the clearer the group preference. Analysis using the score-based approach focuses on score distribution and relative dominance [36]. Analysis focuses on the distribution of weights, such as whether there are criteria that receive a much higher score (dominant) or, conversely, all criteria are balanced.

Analysis using a voting-based approach focuses more on the single winner or the stability of the majority's choice. Weighted analysis of the results is performed by examining the single winner and the strength of their support as a proportion of the vote. If the relative weights are very unequal, it indicates a clear group preference; if they are balanced or a paradox (no Condorcet winner) emerges, further evaluation using other methods is necessary.

Next, a combination of rank-based and score-based aggregation will be used, as they complement each other in capturing the priority structure and intensity of criteria importance. Voting-based aggregation is used as a validation tool to ensure that highly weighted criteria are truly supported by the majority of stakeholders. By positioning voting as a reinforcement mechanism, rather than a primary determinant, the weighting results are more robust, credible, and contextualized to IPCIS implementation at Posyandu.

#### 2.6. Strategic Recommendations

This weighted analysis generates priorities that can be used as a basis for program planning, resource allocation, and the development of evaluation indicators. The criteria with the highest

weighting are recommended as the primary focus for capacity building. Meanwhile, criteria with relatively balanced weighting are still being considered to ensure comprehensive and sustainable implementation of IPCIS.

The recommendations obtained through this quantitative analysis will be further justified through in-depth interviews with cadres, health workers, and posyandu managers. This qualitative approach is expected to provide contextual understanding of the reasons behind the high weighting of a criterion and identify supporting and inhibiting factors in the field. Thus, the recommendations developed are based on aggregate scores and have strong validity because they reflect the empirical conditions of IPCIS implementation at Posyandu.

### 3. RESULT

#### 3.1. Respondent Preferences

A total of 22 respondents participated in this study. The consistency of respondents' answers is checked, and answers are considered invalid if respondents give the same ranking on all criteria. However, only 10 respondents provided valid data. The 10 respondents were adequate because they represented volunteers or cadres, village officials, and health workers. Each respondent expressed their preferences by ranking each criterion. The complete criteria ranking can be seen in Table 2.

Table 2. Criteria Ranking

Decision Maker	Criteria									
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
DM1	1	1	1	1	2	1	1	2	1	1
DM2	1	5	3	1	3	3	2	3	3	2
DM3	3	4	1	1	3	1	1	1	1	1
DM4	2	2	1	1	2	2	1	2	1	1
DM5	1	1	1	2	2	1	1	1	1	1
DM6	1	3	2	1	2	2	1	1	2	1
DM7	1	1	3	1	3	2	2	1	2	1
DM8	1	1	1	3	4	1	1	2	1	1
DM9	1	1	1	1	3	3	1	1	1	1
DM10	1	3	1	2	3	3	2	2	1	1

#### 3.2. Aggregation

##### 3.2.1. Rank-based Aggregation

Table 3 presents the final scores, rankings, and weights for each criterion after preference aggregation using the Borda, Condorcet, and Copeland methods. The results show that criterion C10 consistently ranked first with the highest weight across all three methods, indicating its highest level of importance. Criteria C1 and C7 also ranked high and received relatively high weights, although there were slight differences in order between the methods. Conversely, criteria C5 and C2 tended to be ranked lower with low or near-zero weights, indicating minimal contribution to decision-making.

The differences in weight distribution between methods reflect the characteristics of each aggregation technique in assessing preference strength based on ranking data. In Borda, each increase in ranking always adds points incrementally, so this method tends to produce a smoother weighting spread across multiple criteria. In Condorcet, the assessment is determined more by the ability of one criterion to "beat" another criterion in a majority comparison, allowing for more weighting to be concentrated on the criterion that dominates in the pairing duel. In Copeland, weighting is derived from the difference in wins and losses in the pairing duel so that criteria with frequent wins will rise sharply, while those with frequent losses may decline drastically. Consequently, criteria in the middle can

experience greater weighting fluctuations between methods, as their strength depends on whether they consistently outperform others (Borda) or outperform others in majority battles (Condorcet or Copeland).

Table 3. Rank-based Aggregation

Criteria	Borda			Condorcet			Copeland		
	score	rank	weight (w)	score	rank	weight (w)	score	rank	weight (w)
C1	97	2	0.10	8.0	2	0.18	16.0	2	0.17
C2	88	9	0.09	1.0	9	0.02	2.0	9	0.02
C3	95	6	0.10	4.5	6	0.10	9.5	6	0.10
C4	96	4	0.10	5.5	4	0.12	12.5	4	0.13
C5	83	10	0.09	0.0	10	0.00	0.0	10	0.00
C6	91	8	0.10	2.0	8	0.04	4.0	8	0.04
C7	97	2	0.10	6.5	3	0.14	13.5	3	0.15
C8	94	7	0.10	3.0	7	0.07	6.0	7	0.06
C9	96	4	0.10	5.5	4	0.12	11.5	5	0.12
C10	99	1	0.11	9.0	1	0.20	18.0	1	0.19

### 3.2.2. Score-based Aggregation

Table 4 presents the final scores, rankings, and weights for each criterion obtained through the aggregation process using the mean method. The scores represent the average assessment of each criterion, which is then used to determine the ranking order. Criterion C10 has the highest average score, thus ranking first with the highest weight. Most other criteria have relatively close weights, reflecting a fairly even distribution of importance. These results indicate that the mean method produces stable and non-extreme weights between criteria.

Table 4. Score-based Aggregation

Criteria	Mean		
	score	rank	weight (w)
C1	9.7	2	0.10
C2	8.8	9	0.09
C3	9.5	6	0.10
C4	9.6	4	0.10
C5	8.3	10	0.09
C6	9.1	8	0.10
C7	9.7	2	0.10
C8	9.4	7	0.10
C9	9.6	4	0.10
C10	9.9	1	0.11

### 3.2.3. Voting-based Aggregation

Table 5 presents the final scores, rankings, and weights for each criterion obtained through the aggregation process using the mean method. The scores represent the average assessment of each criterion, which is then used to determine the ranking order. Criterion C10 has the highest average score, thus ranking first with the highest weight. Most other criteria have relatively close weights, reflecting a fairly even distribution of importance. These results indicate that the mean method produces stable and non-extreme weights between criteria.

Table 5. Winner List

	number of wins	Weight (w)
C1	8	0.14
C2	5	0.08
C3	7	0.12
C4	7	0.12
C5	0	0.00
C6	4	0.07
C7	7	0.12
C8	5	0.08
C9	7	0.12
C10	9	0.15

Based on Table 5, the plurality voting analysis shows that criterion C10 is the primary winner because it achieved the highest number of wins (9 wins) compared to the other criteria. In the plurality approach, only the highest number of wins is considered without considering whether the wins exceed the majority threshold, so C10 is directly seen as the most dominant alternative. Criterion C1 is in the next position with 8 wins, but still loses to C10.

Meanwhile, majority voting analysis emphasizes whether a criterion wins more than half of the total possible comparisons. With a total of 9 possible wins, the majority threshold is more than 4.5 wins, so criteria such as C10, C1, C3, C4, C7, and C9 meet the majority criterion. However, C10 remains the strongest because it not only meets the majority but also has the highest margin of victory. This indicates that C10 has the most consistent and strong collective support, both from a plurality and majority voting perspective.

#### 4. DISCUSSIONS

This discussion combines the results of rank-based aggregation (Table 3) and score-based aggregation (Table 4) to produce more robust weights for IPCIS implementation criteria at posyandu. Rank-based aggregation is robust for mapping priority structures and levels of group consensus because it operates on a ranking basis, while score-based aggregation captures the intensity of importance through average values, resulting in more stable weights. When these two results are read together, the criteria that are at the top of the ranking and also have the highest average scores can be designated as the core criteria. This pattern is important because it reduces the risk of overly extreme interpretations: rank results can be “sharp” due to differences in position, while the mean tends to “even out” the weights. By combining the two methods, weighting decisions achieve a more balanced relationship between consensus legitimacy and numerical stability. Overall, the consistency between Tables 2-3 indicates that group preferences are not only consistent in rank but also robust in quantitative assessment. Therefore, the final weights are suitable for use as a basis for recommendations for a phased and risk-oriented IPCIS implementation strategy. Therefore, the final weights are suitable for use as a basis for recommendations for a phased and risk-oriented IPCIS implementation strategy. This is in line with research [26], which states that by utilizing appropriate strategies, countries can move closer to achieving the goal of universal health coverage and improving health outcomes for all.

The criteria that emerged dominantly in the rank-based aggregation also tended to occupy the top positions in the score-based aggregation, indicating a congruence in perceptions among assessors. This means that key implementation factors not only “win” because they are frequently selected at the top of the rankings but are also rated as important with high intensity. Conversely, criteria that are ranked lower in the rank-based aggregation tend to receive lower average scores or are not prominent in the score-based aggregation and therefore can be categorized as supporting factors. The different characteristics of the two approaches help interpret the “middle ranking” phenomenon: in the rank-based aggregation,

it can appear less competitive, but on average, it can still have moderate value and therefore be considered. This distinction is important for the heterogeneous context of posyandu, because factors that are not a top priority can still be obstacles in certain locations. Thus, the combined results allow for grouping criteria into core priority (high-high), middle priority (medium-moderate), and gradual priority (low-low). This grouping is more informative than simply stating the ranking order or average weight. Figure 4 shows the weight of each criterion for the method.

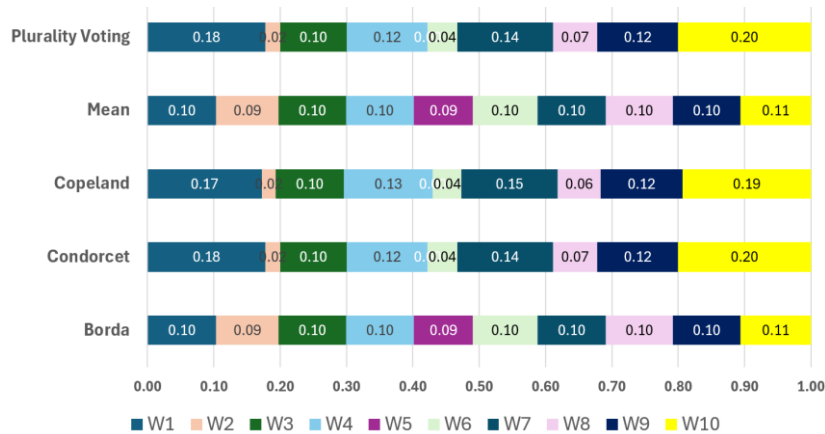


Figure 4. Final Weight of Each Criterion for Each Method

To strengthen these conclusions, testing using voting-based aggregation (Table 4) through majority and plurality voting served as validation based on majority support. Criteria with high weightings in the combination of rank-based and score-based criteria were shown to receive the highest number of votes, thus strengthening their social legitimacy. If a criterion appears moderate on the mean but loses in the voting, this signals that it is considered important by some respondents but has not yet achieved majority consensus. Conversely, criteria that consistently lose in the voting and are also low in both main approaches can be considered low priority in the context of this study. In other words, voting helps to more clearly distinguish between "important but not yet agreed upon" and "not a priority." This strengthening makes the weighting results more defensible when presented to stakeholders (cadres, community health centers, agencies), because they are not only based on averages but also supported by a majority mechanism. The triangulation of these three approaches increases the reliability of the weights and reduces bias due to the characteristics of a particular method.

Based on the weighting of the most dominant and consistent criteria, the IPCIS implementation strategy at posyandu should be structured as a package of interrelated priorities. First, implement a "system trust foundation" strategy by prioritizing security, privacy, and data governance as operational prerequisites before feature expansion. This is in line with research [25], where aspects of security and personal data protection also require serious attention. Second, align the "user capacity building" strategy through tiered training, initial mentoring, and standard operating procedures (SOPs) to ensure core criteria are not compromised by human error. This supports research [8], [9], [10], where the ability of cadres and health workers to operate the system needs to be built through training to ensure they can run the digital health system effectively. Third, promote a "data utilization for services" strategy with a concise dashboard, automated reporting, and feedback to cadres to ensure the system's benefits are felt and adoption increases. This strategy is in line with research [20], which states that the existence of a health dashboard will help monitor community conditions in real-time so that interventions can be carried out more quickly. Fourth, implement a "phased implementation" strategy for lower-weighted criteria (e.g., infrastructure or advanced integration) to avoid burdening investment and changes during the initial phase. Fifth, secure the strategy with a periodic evaluation mechanism based on performance

indicators (data completeness, timeliness of input, and report utilization) so that the criteria's weighting is truly translated into work plans.

The practical implication of these results is that IPCIS success at Posyandu is more effectively achieved if the implementation team prioritizes core criteria with high weighting and majority support. In the initial phase, focusing on strengthening security/governance and human resource readiness will reduce the risk of user rejection, input errors, and trust issues in health data. In the intermediate phase, utilizing data for monitoring and service decisions will increase the system's utility, leading to more sustainable adoption. In the advanced phase, technical aspects with lower weighting can be adaptively improved according to regional readiness, for example, by upgrading devices, improving network stability, or integrating with other platforms. Furthermore, voting results can be used as a basis for policy communication because they demonstrate majority support, facilitating program prioritization and resource allocation. Overall, this robust criteria weighting can serve as a reference for developing a realistic, phased, and dynamic IPCIS implementation roadmap.

## 5. CONCLUSION

The results of this study indicate that a combination of rank-based and score-based aggregation is the most appropriate approach for determining the weighting of criteria for implementing the IPCIS at posyandu. Both approaches are able to capture the priority structure and intensity of criteria importance in a balanced and complementary manner. The consistency of the results between rank-based and score-based aggregation confirms the alignment between the relative consensus and quantitative assessments of stakeholders. The criteria for personal data protection and health information system security (C10) emerged with the highest weighting, indicating that trust and data governance are the most crucial factors in IPCIS implementation. Conversely, the criterion for integrating the IPCIS with other systems (C5) received the lowest weighting, indicating that it serves as a supporting factor that can be developed gradually. Testing with voting-based aggregation backs up these results by showing that the criteria that got the most weight also got the most support. Thus, the resulting criteria weightings are robust and can serve as a reliable basis for formulating IPCIS implementation strategies at posyandu.

The creation of an adaptive weighting model that enables the weights of IPCIS implementation criteria to be adjusted on a regular basis in response to modifications in the system's performance and environment is an urgent area of follow-up study. This strategy is crucial because, if posyandu's system utilization rate rises, the initial implementation phase's criteria priorities may shift. An increasingly adaptable weighting system is necessary due to shifts in user requirements, human resource capability, and health care dynamics. These shifts can be objectively captured by an adaptive weighting model that makes use of system usage data and ongoing user feedback. As a result, this model may help posyandu's IPCIS implementation remain relevant, successful, and sustainable over time. Thus, IPCIS serves as an information technology foundation that enables data-driven adaptation and continuous evaluation of system performance in the context of primary healthcare.

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