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Framework for Prioritizing Solutions in Overcoming Data Quality Problems Using Analytic Hierarchy Process (AHP)

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Abstract

The Central Statistics Agency (BPS) is a government institution that has the authority to carry out statistical activities in the form of censuses and surveys, to produce statistical data needed by the government, the private sector and the general public, as a reference in planning, monitoring, and evaluation of development results. Therefore, providing quality statistical data is very decisive because it will have an impact on the effectiveness of decision making. This paper aims to develop a framework to determine priority of solutions in overcoming data quality problems using the Analytic Hierarchy Process (AHP). The framework is built by conducting interviews and Focus Group Discussion (FGD) on experts to get the interrelationship between problems and solutions. The model that has been built is then tested in a case study, namely the Central Jakarta Central Bureau of Statistics (BPS). The results of the study indicate that the proposed model can be used to formulate solutions to data problems in BPS.

Keywords: Data quality, Analytical hierarchy process, AHP, Central Statistics Agency the Republic of Indonesia.

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Introduction

There are many definitions of data quality, but generally data is considered high quality if the data can be used in operations, decision making, and planning (Redman, 2008). Quality data and information is needed for the organization so that the organization can make decisions quickly and correctly, especially due to the increasing amount of data that must be managed by the organization (Gürdür, El-khoury, & Nyberg, 2018; Haegemans, Snoeck, & Lemahieu, 2019). This raises the need for better data management, which can be seen by the increasing number of frameworks for managing data, such as the Data Management Body of Knowledge (DMBOK) (Haegemans et al., 2019; Mendes, Dong, & Sampaio, 2015; Yeganeh, Sadiq, & Sharaf, 2014).

An organization that requires high quality of data is government institutions, both ministries, non-ministerial government agencies, and local governments, for effective decision making in planning and evaluation for development. The government needs to provide statistical data as an indicator of development, which is used both by the internal government itself and by the private sector to get an accurate picture of the macro environment, which is useful for business planning (Duvier, Neagu, Oltean-dumbrava, & Dickens, 2018). These statistics are also needed by international institutions to obtain an accurate picture of economic and social conditions in Indonesia.

In accordance with Law No. 16 of 1997 and Government Regulation No. 51 of 1999 the Republic of Indonesia, states that the Central Statistics Agency (BPS) is a government institution that has the authority to carry out statistical activities in the form of censuses and surveys, to produce statistical data needed by the government, the private sector and the general public, as a reference in planning, monitoring, and evaluation of development results. Therefore, providing quality statistical data is very decisive because it will have an impact on the effectiveness of decision making.

Providing high quality of data is certainly not easy. In each data life cycle, there are various kinds of sources that cause data to be inadequate, for example the process of data entry is not thorough (Gürdür et al., 2018; Yeganeh et al., 2014). Problems related to these data will certainly differ from one organization to another, depending on how data quality management practices have been carried out by the organization. This requires a continuous process to monitor problems related to data and at the same time formulate ideal solutions to overcome these problems (Gürdür et al., 2018; Yeganeh et al., 2014).

The problem of data quality faced by many organizations is most likely related to rapid technological development (Haug & Arlbjorn, 2010). These rapid technological developments often burden organizations with increasing volumes of data (Haug, & Arlbjorn, 2010). The organization may not know what data may be needed and which is not needed so there is a tendency for the organization to keep all available data. Faced with these conditions the organization must strive to manage incoming data so that it fits the needs of the organization.

It can be concluded that the more data entered, the more complex data management must be carried out by the organization (Haug, & Arlbjorn, 2010).

This study aims to develop a framework needed to map solutions to data problems faced by organizations. The proposed framework was built based on the Analytical Hierarchy Process (AHP) which is a functional hierarchy with the main input of human perception, in our case the data manager in the organization. AHP maps complex and unstructured problems in a structured hierarchy so that these problems can be solved more easily.

To validate the proposed framework, it will be piloted in the Central Jakarta City Administration BPS which has responsibility for providing statistical data for regional and national scope. By using the framework, it is expected that we can set the priority of the solutions in resolving data quality problems at the Central Statistics Agency in the Central Jakarta City Administration.

Literature Review

Data Quality

According to DAMA-DMBOK, data quality is identical to the quality of information, this is because poor data quality will produce inaccurate information and poor business performance (Brackett & Earley, 2009). Data cleaning can result in improved data quality but will have a short-term impact and are expensive, so this solution has not been able to overcome the root causes of poor data quality. More rigorous data quality programs or strategies are needed to provide economic solutions to improve data quality and integrity (Brackett & Earley, 2009).

In data quality strategy, this involves more than just correcting data. Data quality programs or strategies involve management life cycles for data creation, transformation, and transmission to ensure that the information produced meets the needs of all data consumers in the organization (Brackett & Earley, 2009). Management and improvement of data quality and determining the best way to measure, monitor, control, and report data quality depends on identifying business needs (Brackett & Earley, 2009). Poor decision making could be the serious impact caused by poor data quality of an organization (Keller & Staelin, 1987; Chengalur-Smith, Ballou, & Pazer, 1999; Raghunathan, 1999; Jung, Olfman, Ryan, & Park, 2005; Shankaranarayanan & Cai, 2006; Ge & Helfert, 2008) and finally risks organizational performance (Redman, 1998; Fisher & Kingma, 2001; Eppler & Helfert, 2004; Slone, 2006).

Barriers for Achieving High Quality of Data

In line with the business objectives of the organization, the challenge for organizations is to be able to minimize poor quality of data that requires strategic and tactical focusing collaboration and information technology (IT) collaboration (Groot, 2017). Table 1 below presents the barrier of data quality management from several previous studies (Umar, 1999; English, 1999; Xu, Nord, Brown, & Nord, 2002; Haug and Arlbjorn, 2010). Poor data management encourages the emergence of silo data in the organization causing redundant data stored, managed, and processed.

Table 1. Barriers of high quality of data

Barriers of high quality of data	Umar et al. (1999)	English (1999)	Xu et al. (2002)	Lee et al. (2006)	Haug & Arlbjorn (2010)
No dedicated roles and responsibilities	✓		✓	✓	✓
Lack of identification of data quality owners	✓		✓		
Inefficient organizational procedures	✓		✓	✓	
Lack of scheduling scenarios	✓				
Lack of reward and punishment system	✓	✓			✓
Lack of training and education	✓	✓	✓		✓
Lack of top management support		✓	✓		
Poor change management			✓		
Poor employee relations			✓		
Lack of supporting tools;				✓	
Lack of appropriate technologies				✓	
Lack of data control routines;					✓
Lack of user-friendliness of the software used to manage data.					✓

Analytical Hierarchy Process (AHP)

The Analytical Hierarchy Process (AHP) model first proposed by Thomas L. Saaty (1977). It is a multi-criteria decision-making technique to help decision makers when dealing with complex problems characterized by many subjective and alternative criteria conflicts (Wibowo, Dayanti, Hidayanto, Etivani, & Phusavat, 2018). AHP is a theory of measurement that is used to find the ratio scale by making pairwise comparisons between factors (Efraim, 2011). The AHP modeling process can be divided into the following 6 (six) steps (Wang, Yan, Zhou, & Li, 2015):

١. Define the problem and the goal.
٢. Modeling the hierarchical structure, which is used to model the criteria considered in making decisions.
٣. Form an assessment matrix for each hierarchy. This step is to identify priorities among all elements by making pairwise comparisons based on certain criteria from the

previous hierarchy. The comparison process for measuring priority uses a comparative scale as in Table 2.

Table 2. Scale of pairwise comparison value

Importance Level	Definition
1	Both elements are equally important
3	One element is a little more important than the other elements.
5	One element is more important than the other elements.
7	One element is clearly more important than other elements.
9	One element is absolutely important than the other elements.
2, 4, 6, 8	Values between two adjacent consideration values
Reverse	If element *i* has one of the numbers above when compared to element *j*, then *j* has the opposite value when compared to element *i*

١. Synthesis of priority, which is looking for the eigen vector value to get a series of overall priorities for each hierarchy.

٢. Check the logical consistency, to determine the level of consistency of the results of the assessment. In this step, it is necessary to test whether the deviation of the assessment matrix is acceptable. This assessment matrix applies when consistency is accepted, otherwise the assessment matrix must be revised. Consistency is determined using the eigen vector value. Consistency Index (CI) can be calculated using equation (1). Then, the level of consistency can be checked using a Consistency Ratio (CR) value which can be calculated by equation (2). When the CR is not more than 0.1, the matrix assessment results are accepted. If not, the assessment matrix is inconsistent, and must be revised and improved.

٣. The consistency of a standard index called a random consistency index (RI) is shown in Table 3 where n refers to the number of elements. By knowing CI, CR can be calculated by comparing it to one RI that corresponds to the number of elements.

٤. Determine priority decisions based on the results of the above process.

1) $$CI = (\lambda_{max} - n) / (n - 1)$$

2) $$CR = CI / IR$$

CI = Consistency Index

λ_{max} = Maximum eigen value

n = Number of elements

CR = Consistency Ratio

IR = Index Ratio

Table 3. Random Index (RI)

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

The Proposed Approach

The development of the framework comprises of five stages as can be seen in Figure 1.

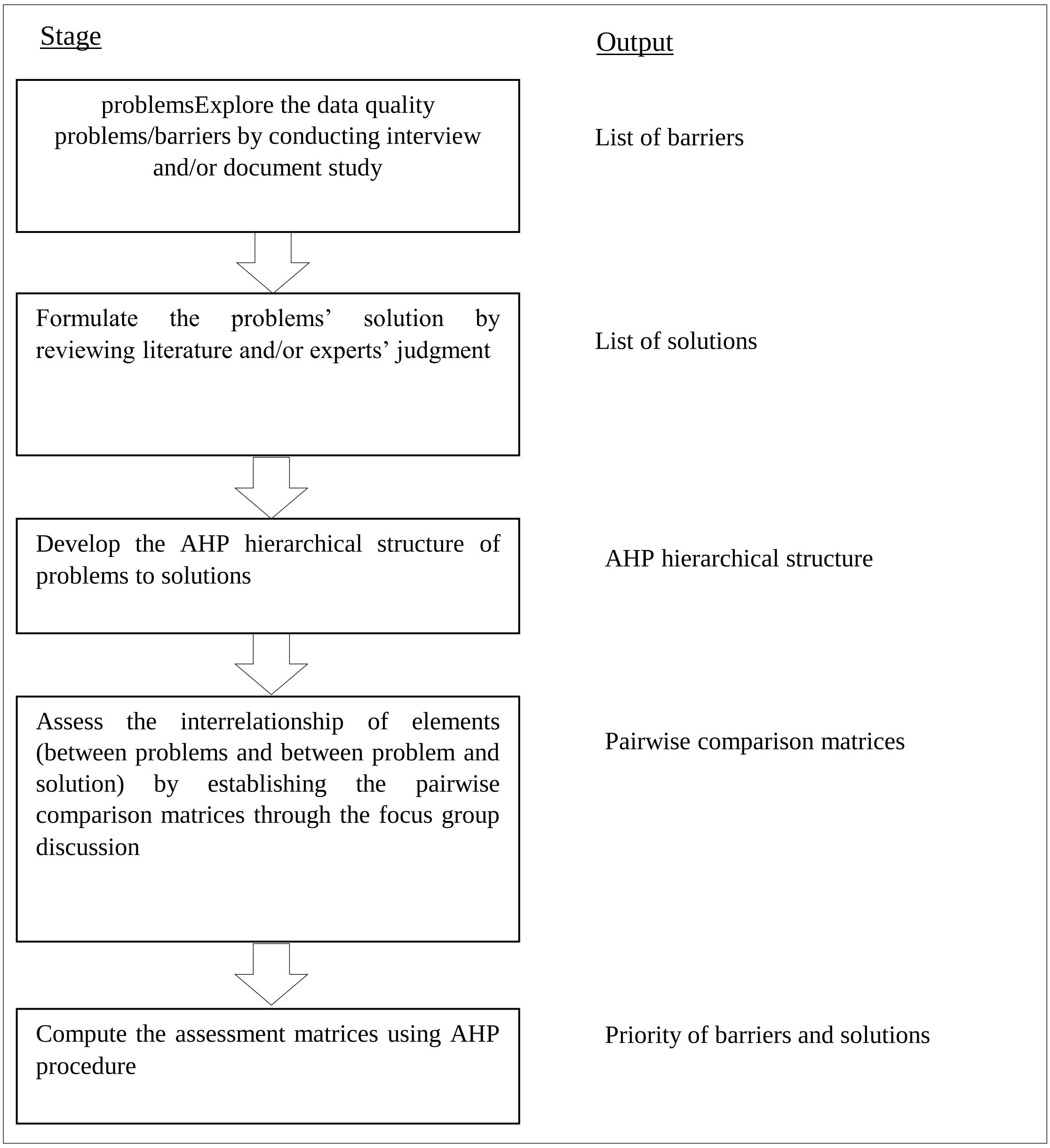

Figure 1. Proposed stages for framework development

In the first stage, the organization needs to investigate the barriers/problems faced by the organization by conducting interviews with the key staffs involved in the data life cycle, from the operational level who gathers the data to the strategic level who uses the data for decision making. Also, the document study is important as part of data triangulation. In the second stage, we need to interview the key stakeholders in the organization as well as the experts to formulate the strategies or solutions recommended to solve the barriers related to the data quality. In the third stage, based on the problems and solutions obtained, we can establish an AHP hierarchical structure. The hierarchical structure contains the list of problems as the criteria and the list of solutions as the alternatives, reflecting the mapping of solutions for overcoming barriers. In the fourth stage, we need to conduct focus group discussion or Delphi method to establish the assessment matrices. The assessment matrices contain the pairwise comparison between problems or between problem and solution, reflecting the relative importance of one problem to another one or the relative importance of a solution for overcoming a barrier. In the last stage, we compute the assessment matrices according to the AHP procedure to obtain the priority of solutions for overcoming barriers faced by the organization.

Application of the Framework

This study will use a case study approach at the Jakarta Administrative Bureau of Statistics (BPS) and determine the priority of proposed solutions to overcome problems in its data quality. The process of collecting data in this study was carried out in 5 (five) stages as we outlined in our proposal. In the first and second stages, we interviewed 8 (eight) people representing 4 (four) sections, namely the Social Statistics section, the Distribution Statistics section, the Production Statistics section, and the Integration of Statistical Dissemination Processing section. Each section is represented by a Section Head with each working period above 10 (ten) years and an executive staff with a working period ranging from 5 (five) to 15 (fifteen) years to validate the list of problems and proposed solutions offered as well as providing input relating to problems and solutions.

Berdasarkan hasil identifikasi barriers of high quality of data dari beberapa penelitian sebelumnya yang disajikan pada Tabel 1, penelitian ini membagi barriers of high quality of data menjadi tiga kategori yaitu Human, Technology, dan Data Source untuk selanjutnya divalidasi oleh stakeholders terkait. The results of this stage are a list of problems and solutions that have been validated by BPS as can be seen in Table 4 and Table 5. Thus, we developed the AHP hierarchy as can be seen in Figure 2. In the fourth stage, we conducted a Focus Group Discussion (FGD) with 8 (eight) people from the previous stage to obtain data on the level of interrelationship between problems and the level of interrelationships between problems and solutions. The results of this FGD were processed using the AHP.

Table 4. Barriers for achieving quality data

Code	Sub Category
Category: Human	
H1	Staff planning is not optimal
H2	Unskilled staffs
H3	Weak coordination
H4	Lack of staffs
Category: Technology	
T1	Timeliness of release is not optimal
T2	Data processing application system that is not yet integrated
T3	The challenge of paper-based data accuracy
Category: Data Sources	
D1	Lack of respondents' understanding
D2	Low response rate
D3	Lack of openness of respondents in filling out the form
D4	High respondent mobility

Table 5. Proposed solutions

Code	Solutions
S1	Optimizing human resource management through staffing and career planning (Purnama, 2016)
S2	Employee placement based on skills, expertise and educational background (Haug and Arlbjorn, 2010)
S3	Effective communication between units to improve data team performance (Hassal, 2009)
S4	The optimal addition of the number of workers (staff) adjusted for load work (Abidin, 2016)
S5	Use middleware software to integrate multiple application systems (Laudon & Laudon, 2016)
S6	Use a mobile-based application to speed up and improve the accuracy of data collection (Laudon & Laudon, 2016)
S7	Inform the BPS program and increase public awareness on the BPS program (Mugo et al., 2017)
S8	Study the activity trends and mobility factors of the respondents to be surveyed so that they can make effective and efficient survey planning (Lee, 1966)

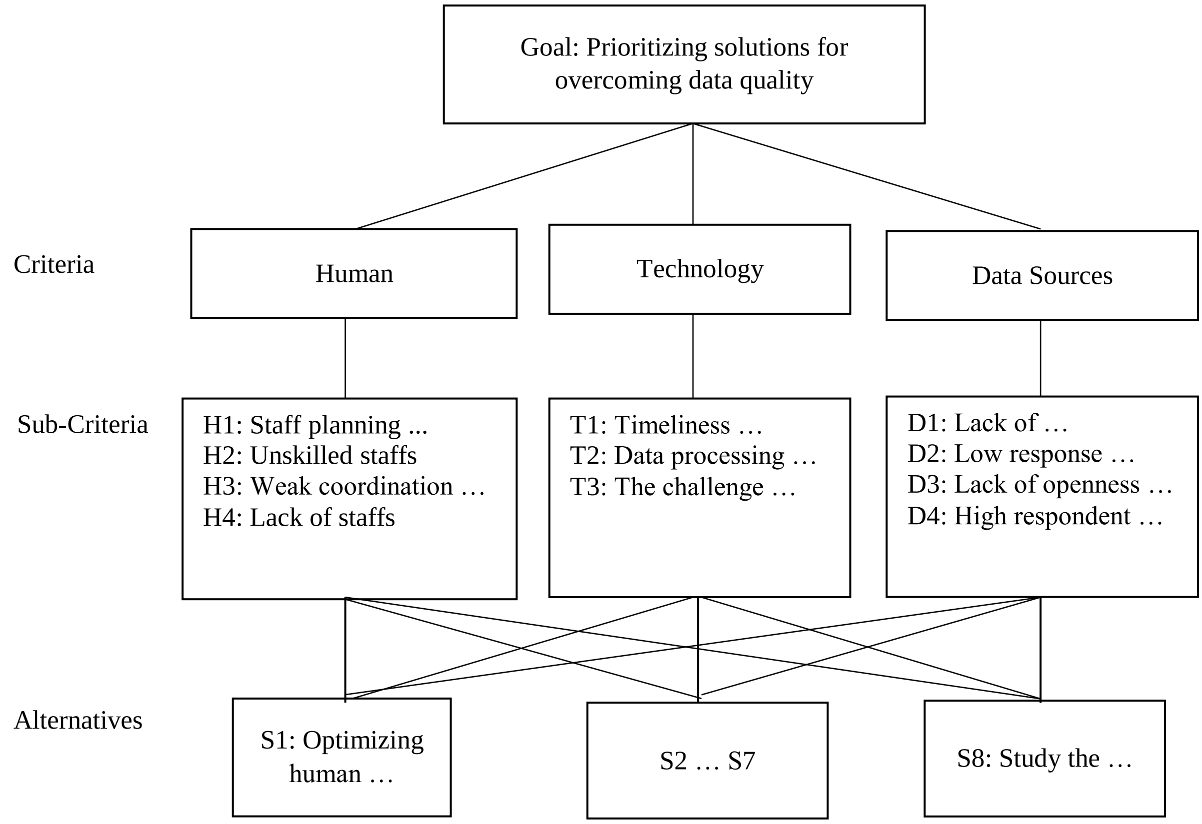

Figure 2. The AHP hierarchyMethod

The AHP starts by establishing the assessment matrices which contain pairwise comparison between criteria (problems) and criteria and alternatives (solutions). In our case, as can be seen in Figure 2, the criteria of barriers are classified into three, namely: Human, Technology, and Data Sources. Each criterion is divided into sub-criteria, for example, the Human criteria contains four sub-criteria. The proposed solutions became the alternatives in the AHP context. Thus, our key informants were required to fill the following: one assessment matrix (pairwise comparison) for criteria comparisons, three assessment matrices for sub-criteria comparisons in each criterion, and eleven assessment matrices for solutions comparisons (comparing the preferred solutions to solve a problem). After making pairwise comparisons of each element of the problems and solutions, the eigen vector can be determined by normalizing the pairwise comparison matrix so that results are obtained as in Table 6 to Table 13. All values of the consistency ratio or CR are less than 0.1. Therefore, matrix assessment results are accepted. In the same way, we also computed the eigen vector values for the Technology and Data Sources sub-category. For the sake of the simplicity, we did not report the values here. In this study, the Microsoft Excel 2010 application is used to calculate eigen vector (ev) values.

Table 6. Eigen vector calculation results (ev) of criteria comparisons

	Human	Technology	Data Sources	ev
Human	0.097	0.231	0.091	0.139
Technology	0.032	0.077	0.091	0.067
Data Sources	0.871	0.692	0.818	0.794

Table 7. Eigen vector calculation results (ev) of sub-criteria comparisons in Human category

	H1	H2	H3	H4	ev
H1	0.119	0.278	0.034	0.750	0.041
H2	0.024	0.056	0.026	0.50	0.005
H3	0.833	0.500	0.235	0.050	0.056
H4	0.024	0.167	0.705	0.150	0.036

Table 8. Eigen vector calculation results (ev) of sub-criteria comparisons in Technology category

	T1	T2	T3	ev
T1	0.231	0.333	0.217	0.017
T2	0.077	0.111	0.130	0.017
T3	0.692	0.556	0.652	0.042

Table 9. Eigen vector calculation results (ev) of sub-criteria comparisons in Data Source category

	D1	D2	D3	D4	ev
D1	0.063	0.088	0.044	0.029	0.045
D2	0.438	0.618	0.662	0.618	0.463
D3	0.313	0.206	0.221	0.265	0.199
D4	0.188	0.088	0.074	0.088	0.087

Table 10. Eigen vector calculation results (ev) of solutions comparisons with respect to H1 sub-category

	S1	S2	S3	S4	S5	S6	S7	S8	ev
S1	0.434	0.549	0.469	0.375	0.318	0.318	0.318	0.318	0.016
S2	0.145	0.183	0.281	0.225	0.227	0.227	0.227	0.227	0.009
S3	0.087	0.061	0.094	0.225	0.136	0.136	0.136	0.136	0.005
S4	0.087	0.061	0.031	0.075	0.136	0.136	0.136	0.136	0.004
S5	0.062	0.037	0.031	0.025	0.045	0.045	0.045	0.045	0.002
S6	0.062	0.037	0.031	0.025	0.045	0.045	0.045	0.045	0.002
S7	0.062	0.037	0.031	0.025	0.045	0.045	0.045	0.045	0.002
S8	0.062	0.037	0.031	0.025	0.045	0.045	0.045	0.045	0.002

Table 11. Eigen vector calculation results (ev) of solutions comparisons with respect to H2 sub-category

	S1	S2	S3	S4	S5	S6	S7	S8	ev
S1	0.183	0.145	0.281	0.188	0.250	0.250	0.250	0.250	0.001
S2	0.549	0.434	0.469	0.313	0.350	0.350	0.350	0.350	0.002
S3	0.061	0.087	0.094	0.188	0.150	0.150	0.150	0.150	0.001
S4	0.061	0.087	0.031	0.063	0.050	0.050	0.050	0.050	0.000
S5	0.037	0.062	0.031	0.063	0.050	0.050	0.050	0.050	0.000
S6	0.037	0.062	0.031	0.063	0.050	0.050	0.050	0.050	0.000
S7	0.037	0.062	0.031	0.063	0.050	0.050	0.050	0.050	0.000
S8	0.037	0.062	0.031	0.063	0.050	0.050	0.050	0.050	0.000

Table 12. Eigen vector calculation results (ev) of solutions comparisons with respect to H3 sub-category

	S1	S2	S3	S4	S5	S6	S7	S8	ev
S1	0.101	0.101	0.091	0.141	0.318	0.101	0.141	0.139	0.006
S2	0.101	0.101	0.091	0.141	0.227	0.101	0.141	0.139	0.006
S3	0.507	0.507	0.455	0.328	0.136	0.507	0.328	0.250	0.024
S4	0.034	0.034	0.065	0.047	0.136	0.034	0.047	0.083	0.003
S5	0.101	0.101	0.091	0.141	0.045	0.101	0.141	0.139	0.006
S6	0.101	0.101	0.091	0.141	0.045	0.101	0.141	0.139	0.006
S7	0.034	0.034	0.065	0.047	0.045	0.034	0.047	0.083	0.003
S8	0.020	0.020	0.051	0.016	0.045	0.020	0.016	0.028	0.001

Table 13. Eigen vector calculation results (ev) of solutions comparisons with respect to H4 sub-category

	S1	S2	S3	S4	S5	S6	S7	S8	ev
S1	0.115	0.115	0.136	0.109	0.115	0.115	0.115	0.136	0.004
S2	0.115	0.115	0.136	0.109	0.115	0.115	0.115	0.136	0.004
S3	0.038	0.038	0.045	0.065	0.038	0.038	0.038	0.045	0.002
S4	0.346	0.346	0.227	0.326	0.346	0.346	0.346	0.227	0.011
S5	0.115	0.115	0.136	0.109	0.115	0.115	0.115	0.136	0.004
S6	0.115	0.115	0.136	0.109	0.115	0.115	0.115	0.136	0.004
S7	0.115	0.115	0.136	0.109	0.115	0.115	0.115	0.136	0.004
S8	0.038	0.038	0.045	0.065	0.038	0.038	0.038	0.045	0.002

Based on the eigen vector calculation above, it can be used as data to create a new matrix to obtain the final weight of each solution. The final weighting results are described in Table 13.

Table 14. Final weighting results of the proposed solutions (priority)

Sub-category	Weight							
	S1	S2	S3	S4	S5	S6	S7	S8
M1	0.016	0.009	0.005	0.004	0.002	0.002	0.002	0.002
M2	0.001	0.002	0.001	0.000	0.000	0.000	0.000	0.000
M3	0.006	0.006	0.024	0.003	0.006	0.006	0.003	0.001
M4	0.004	0.004	0.002	0.011	0.004	0.004	0.004	0.002
T1	0.001	0.002	0.002	0.000	0.001	0.006	0.004	0.001
T2	0.001	0.001	0.001	0.000	0.003	0.001	0.000	0.000
T3	0.003	0.005	0.004	0.004	0.008	0.015	0.003	0.001
D1	0.006	0.005	0.003	0.002	0.001	0.003	0.018	0.007
D2	0.052	0.061	0.034	0.017	0.016	0.003	0.183	0.071
D3	0.011	0.011	0.031	0.006	0.013	0.017	0.082	0.028
D4	0.006	0.006	0.003	0.013	0.006	0.009	0.020	0.025
Total weight	0.107	0.112	0.110	0.060	0.060	0.093	0.319	0.138
Ranking	5	3	4	8	7	6	1	2

Based on Table 14, the results show that the S7 is the solution that ranks first with a weight of 0.319 followed by S8 in the second with a weight of 0.138.

Conclusion

This research has attempted to develop a framework for prioritizing solutions in overcoming problems/barriers in data quality. The framework was built using Analytical Hierarchy Process (AHP) and have been applied at the Central Jakarta Central Bureau of Statistics (BPS). We have been able to identify eight proposed solutions to address the issue of data quality at BPS that can be categorized into three: human, technology, and data source. Based on the AHP calculation, it was found that ‘Inform the BPS program and increase public awareness on the BPS program ' (S7) as the first rank was the best solution followed by 'Study the activity trends and mobility factors of the respondents to be surveyed so that they can make effective survey planning and efficient '(S8) as a second rank solution, and ‘Employee placement based on skills, expertise and educational background’ (S2) as the third rank solution. In the future, we plan to extend the framework by involving more experts so that we can develop a more general framework that can be adapted by any organizations to prepare their data quality programs.

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