International Journal of Research in Engineering and Science (IJRES)
ISSN (Online): 2320-9364, ISSN (Print): 2320-9356
www.ijres.org Volume 13 Issue 5 ǁ May 2025 ǁ PP. 45-53

Risk Factor Analysis and Risk Response of *S*elf-managed Environmental Scale Infrastructure Project in Palu City

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Abstract
One of the implementation models of self-managed project is Environmental Scale Infrastructure which aims to reduce the infrastructure gap around permanent housing, increase community capacity and participation in development and strengthen basic service infrastructure and the economy that is oriented towards reducing disaster risk in areas affected by the 2018 disaster in Central Sulawesi. Self-managed project work certainly has risks that can hinder project implementation. This study aims to identify emerging risk factors, analyze the dominant risk factors and risk response of self-managed environmental scale infrastructure*. The results of risk identification from the literature study obtained 7 risk factors with 23 sub-factors. The analysis results indicate that there are four dominant risk factors: the planning factors 48.741%, the material and equipment factors 8.582%, the management factors 7.208%, and the social factors 6.063%. The total influence of these factors reaches 70.594%, while the remaining 29.406% is influenced by other factors with less significant impact. The most dominant risk factor is the planning factors, which has the highest variance value of 48.741%. Within this factor, the variable lack of understanding of the implementation and technical guidelines contributes the most significantly, accounting for 5.41% of the total variance. In terms of risk response, it is crucial to ensure that the implementation and technical guidelines are clearly and comprehensively formulated and easily understood, while also providing socialization and training for the self-managed implementers.*
Keyword: *Risk, Self-managed Project, Factor Analysis*

Date of Submission: 28-04-2025 Date of acceptance: 07-05-2025

I. INTRODUCTION

Infrastructure development plays a critical role in accelerating economic growth, reducing inequality, and improving public welfare, particularly in developing countries [1]. Traditionally, infrastructure projects have been implemented through centralized, top-down approaches. However, these models often fail to address local needs effectively and lack community engagement, which can hinder sustainability and ownership [2]. In response, Indonesia has adopted self-managed approaches to infrastructure development**.** Self-managed refers to a method of project implementation that does not involve third-party contractors but is instead carried out by government institutions, community groups, or civil society organizations, in accordance with applicable regulations [3]. Self-managed models, for example, have been widely promoted by international development agencies as a means to increase efficiency, transparency, and accountability while also empowering local populations [4]. Nevertheless, the implementation of self-managed infrastructure projects continues to face a number of risks and challenges, including limited technical capacity, inadequate oversight, and difficulties in financial and administrative management [5]. Therefore, understanding the key risk factors and applicable mitigation strategies is crucial for enhancing the effectiveness of self-managed infrastructure implementation, ensuring that development efforts are more efficient, inclusive, and sustainable.

II. LITERATUR REVIEW

Here are several relevant concepts and literature studies that support the research objects:

2.1 Self-managed Project

Self-managed Project approaches have been increasingly adopted in infrastructure projects, particularly in developing countries, as an alternative to centralized, top-down implementation models [6]. These approaches emphasize active community participation in planning, execution, and monitoring phases, and are often applied to rural infrastructure such as roads, water systems, sanitation, and public buildings [7].

2.2 Project Risk

A risk is defined as the potential for complications and problems with respect to the completion of a project and the achievement of a project goal [8] and as an uncertain future event or condition with the occurrence rate of greater than 0% but less than 100% that has an effect on at least one of project objectives (i.e., scope, schedule, cost, or quality, etc.). In addition, the impact or consequences of this future event must be unexpected or unplanned [9]. The sources of risk in construction and project-based industries include inherent uncertainties and issues related to fluctuating profit margins, the competitive bidding process, weather variability, job-site productivity, political instability, inflation, contractual obligations, and market competition [10]. To successfully carry out a construction project, it is essential to implement a comprehensive risk management strategy covering various aspects like finances, schedule, safety, quality, and environmental sustainability [11]. Systemic project risk management has an effect on the project success. It is found that there is a strong relationship between the amount of risk management efforts undertaken in a project and the level of the project success [12]. Existing approaches may be summarized into a four phase process for effective project risk management, i.e., identifying risks, assessing risks, responding risks, and monitoring and/or reviewing risks. Identifying risks is the first step which determines which risk components may adversely affect which project objectives and documents their characteristics [13].

2.3 Factor Analysis

Factor analysis is a statistical technique used to uncover the latent structure underlying a set of observed variables. It aims to identify a smaller number of unobservable factors that explain the patterns and correlations observed in the data [14]. The fundamental assumption of factor analysis is that the observed variables are influenced by a smaller number of underlying factors [15]. Factor analysis helps to minimize the dimensionality of the data and offers insights into the latent structure by investigating the correlations between the observed variables [16].

The first step in factor analysis involves identifying the variables to be studied. To assess the suitability of the dataset for factor analysis, the Measure of Sampling Adequacy (MSA) and Bartlett's Test of Sphericity are employed. These tests help determine whether the correlation matrix is appropriate for factor extraction. Once the data meets the necessary criteria, the next stage—factor extraction or factoring—is conducted to identify the underlying structure among variables [17].

2.4 Risk Response

Risk response is considered to be a very important stage in risk management because if it's finding the projects lead to create opportunities and decrease the threats that indicate how well are the managers [18]. To be specific, the plan of risk response has the possibility to make the conditions which considered to be essential for optimal identification of risk and evaluation, hence, the action of risk response should be designed, classified and justified on systematic principle [19].

To determine appropriate responses to identified risks, a combination of methods was employed, including a comprehensive literature review, focused discussions, and interviews with facilitators, self-management practitioners, and pre-selected experts. These methods were aimed at exploring feasible risk response strategies corresponding to the risks previously identified through risk analysis [20].

III. RESEARCH METHODS

A questionnaire survey was used to elicit the attitude of OMS (Organisasi Masyarakat Setempat), Facilitator, and Consultants towards the factors affecting the self-managed environmental scale infrastructure projects. Using a purposive sampling approach, the researcher deliberately chose participants based on predetermined characteristics of the sample [21]. This research used Likert scale with options strongly agree (5), agree (4), neutral (3), disagree (2) and strongly disagree (1). Opinions from 40 participants were collected by the Likert scale survey, which assessed seven major factors. These factors included: materials, equipment, human resources, scope and documents of work, force majeure, implementation and management.

IBM SPSS Statistics was the tool for the analysis the factors. Factor analysis is a statistical technique that extracts the maximum shared variance from a set of observed variables and represents it through standardized scores. This method is commonly used to reduce a large number of variables into a smaller set of underlying factors, thereby simplifying data interpretation and analysis [22]. Principal Component Analysis (PCA) is one of the widely used methods for factor extraction [23]. Also, a Varimax rotation is used to simplify a sub-space into few major items. Rotated Component Matrix is a Key output of PCA. Kaiser-Meyer-Olkin (KMO) Test is the measure of the suitability of the data for Factor Analysis [23]. The KMO Measure of Sampling Adequacy may be a statistic that indicates the proportion of variance within the variables which may be caused by underlying factors. Bartlett's test of sphericity tests the hypothesis that the correlation matrix is an identity matrix [24].

IV. RESULTS AND DISCUSSION

4.1 Characteristics of Respondents

Table 4.1: Demographic characteristics of respondents

Characteristic	Frequency	Percentage
Education		
SLTA	5	13%
D1-D3	2	5%
S1	30	75%
S2	3	8%
Work Experience		
0-5 Tahun	25	63%
6-10 Tahun	7	18%
11-15 Tahun	3	8%
16-20 Tahun	3	8%
> 21 Tahun	2	5%
Gender		
Male	20	50%
Female	20	50%

From the results of the respondents' characteristics, it can be seen that the respondent based on the education of 40 respondents, the majority hold a Bachelor's degree (S1), with 30 individuals (75%), indicating a well-educated group of participants. This is followed by high school graduates (SLTA) at 13%, Master's degree holders (S2) at 8%, and diploma holders (D1–D3) at 5%. In terms of work experience, the majority of respondents (63%) have 0–5 years of experience, suggesting that many are relatively early in their professional careers. This is followed by 18% with 6–10 years of experience, while the rest have more than 10 years of experience, each category making up 8% or less. Regarding gender, the distribution is balanced, with 50% male and 50% female respondents.

4.2 Validity Test

Validity test was conducted to examine the significance of the correlation coefficient (Pearson correlation) at significant level (α) of 0.05. The test used two-sided tests with significance level of 0.05. The test criteria were 1) if $r_{count} > r_{table}$, the variable was declared valid; and 2) when $r_{count} < r_{table}$, the variable was declared not valid. Since all instruments in the validity test had r_{count} significance (α) 5% > r table with 5% significance, the variable used was valid [21].

An r_{table} of 0.312 was produced after researchers used a significance level (α) = 0.05 to examine the outcomes of 40 respondents' answers.

Table 4.2 Validity Test Results

Variable	Indicator	Sig.*(2-Tailed)*	α	r_{count}	r_{table} (*r Product moment*)	Criteria
Materials (X1)	X1.1	0,000	0,05	0.856	0,312	Valid
	X1.2	0,000		0.835		Valid
	X1.3	0,000		0.727		Valid
	X1.4	0,000		0.832		Valid
Equipment (X2)	X2.5	0,000		0.793		Valid
	X2.6	0,000		0.860		Valid
	X2.7	0,000		0.850		Valid
Human resources (X3)	X3.8	0,000		0.913		Valid
	X3.9	0,000		0.823		Valid
	X3.10	0,000		0.886		Valid
	X3.11	0,000		0.695		Valid
	X3.12	0,000		0.870		Valid
Scope and Documents of work (X4)	X4.13	0,000		0.769		Valid
	X4.14	0,000		0.884		Valid
	X4.15	0,000		0.892		Valid
Force Majeure(X5)	X5.16	0,000		0.934		Valid
	X5.17	0,000		0.930		Valid
Implementation (X6)	X6.18	0,000		0.943		Valid
	X6.19	0,000		0.933		Valid
Management (X7)	X7.20	0,000		0.832		Valid
	X7.21	0,000		0.916		Valid
	X7.22	0,000		0.815		Valid
	X7.23	0,000		0.825		Valid

From the results of the validity test calculation in the table above, it can be seen that $r_{count} > r_{table}$, (0.312) all indicators on the questionnaire are declared valid, so that the data on each indicator can be analyzed further.

4.3 Reliability Tests

Reliability test is conducted to determine the consistency of a questionnaire. Reliability test in this study, which examined the consistency of the research variable, used Cronbach's alpha values. When Cronbach's Alpha > 0.60, the variable is reliable [21]. However, the variable in question is considered unreliable if its Cronbach's Alpha < 0.60.

Table 4.2 Reliability Test Results

Variable	*Cronbach's Alpha*	*Cronbach's Alpha required*	Criteria
Materials (X1)	0.827	> 0,60	Reliable
Equipment (X2)	0.782	> 0,60	Reliable
Human resources (X3)	0,895	> 0,60	Reliable
Scope and Documents of work (X4)	0,801	> 0,60	Reliable
Force Majeure(X5)	0,848	> 0,60	Reliable
Implementation (X6)	0,862	> 0,60	Reliable
Management (X7)	0,868	> 0,60	Reliable

As shown in Table 4.2, all of the Cronbach's Alpha > 0.60, It follows that all the variables are reliable.

4.4 KMO (Keiser Meyer Olkin) and Bartlett's Test

To test the suitability of data for factor analysis, the Kaiser-Meyer-Olkin (KMO) and Bartlett's Test of Sphericity were used. A KMO > 0.60 indicates adequate sampling, while a significant Bartlett's Test < 0.05.

Table 4.3 Results of the KMO Test and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.746
Bartlett's Test of Sphericity	Approx. Chi-Square	662.959
	df	210
	Sig.	0.000

The KMO measure of sampling adequacy (MSA) results is 0.746. This indicates good partial correlation. The Bartlett's test of Sphericity result is 0.0001 which means very significant.

4.5 MSA (Measure of Sampling Adequacy) Test

The MSA test is a test used to measure homogeneity between variables and filter between variables so that only qualified variables can be processed further. A values range from 0.5 to 1.0, with the following criteria: MSA = 1 indicates that the variable can be perfectly predicted by other variables, MSA ≥ 0.5 indicates the variable is acceptable and can be analyzed further, MSA < 0.5 suggests the variable cannot be predicted and should be excluded from further analysis.

Table 4.4 Anti-image correlation values after the variables X5.1 and X5.2 was removed from the MSA test

Item	Anti-image correlation
X1.1	0,723
X1.2	0,826
X1.3	0,858
X1.4	0,812
X2.1	0,734
X2.2	0,756
X2.3	0,726
X3.1	0,787
X3.2	0,730
X3.3	0,794
X3.4	0,676
X3.5	0,720
X4.1	0,851
X4.2	0,789
X4.3	0,729
X6.1	0,562
X6.2	0,724
X7.1	0,701
X7.2	0,700
X7.3	0,845

Item	Anti-image correlation
X1.1	0,625

From the MSA Test table 4.4 the MSA test results indicate that several variables have MSA values below 0.5, suggesting that they are not suitable for factor analysis. Therefore, these variables must be removed from subsequent MSA evaluations. After sequentially eliminating the variables that do not meet the MSA threshold, the remaining dataset consists of variables with factor loading values greater than 0.5, indicating their adequacy for further analysis.

4.6 Communality Estimation

The factoring or extraction process is the process of separating variables that meet the correlation of the MSA value, where a variable is said to be correlated if the MSA value > 0.5. The method used is Principal Components Analysis (PCA). The number of variables to be extracted can be seen in table 4.5 of the contribution of the extracted variables.

Table 4.5 Communality Estimation Analysis Results

Communalities		
	Initial	Extraction
X1.1	1.000	0.553
X1.2	1.000	0.728
X1.3	1.000	0.539
X1.4	1.000	0.657
X2.1	1.000	0.748
X2.2	1.000	0.681
X2.3	1.000	0.617
X3.1	1.000	0.775
X3.2	1.000	0.658
X3.3	1.000	0.816
X3.4	1.000	0.547
X3.5	1.000	0.743
X4.1	1.000	0.679
X4.2	1.000	0.676
X4.3	1.000	0.724
X6.1	1.000	0.743
X6.2	1.000	0.852
X7.1	1.000	0.737
X7.2	1.000	0.836
X7.3	1.000	0.760
X7.4	1.000	0.757

Table 4.5 contribution of extracted variables shows the value of the variables to the formed factors. The greater the contribution of a variable, the closer the relationship with the formed factors.

4.7 Factor Extraction

The next analysis is factor extraction. Factor extraction was conducted to transform original items into new correlating factors. The total variables that have a correlation are 21 variables, then in Table 4.6 the total extraction results, the number of extraction result factors will be seen.

Table 4.6 Total Variance Explained

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	10.236	48.741	48.741	10.236	48.741	48.741	5.777	27.511	27.511
2	1.802	8.582	57.323	1.802	8.582	57.323	3.545	16.880	44.391
3	1.514	7.208	64.531	1.514	7.208	64.531	3.240	15.429	59.820
4	1.273	6.063	70.594	1.273	6.063	70.594	2.263	10.774	70.594
5	0.971	4.623	75.217						
6	0.865	4.119	79.336						
7	0.736	3.506	82.842						
8	0.608	2.897	85.738						
9	0.540	2.569	88.308						

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
10	0.508	2.417	90.725						
11	0.431	2.052	92.777						
12	0.344	1.638	94.415						
13	0.272	1.297	95.712						
14	0.219	1.045	96.757						
15	0.198	0.941	97.697						
16	0.143	0.682	98.380						
17	0.115	0.550	98.929						
18	0.109	0.517	99.446						
19	0.056	0.267	99.713						
20	0.034	0.160	99.873						
21	0.027	0.127	100.000						

From 21 extracted variables, 4 factors were formed as seen in Table 4.6 Number of Extraction Result Factors. Where 4 indicators possess eigenvalues of higher than 1. With a rather high cumulative total variance number of 70.594%. In addition to the total variance table, there is also a graph that explains the basis of calculation in determining the number of factors, seen in the Scree Plot graph. The shape of the Scree Plot graph that corresponds can be seen in Figure 4.1 Scree Plot as follows:

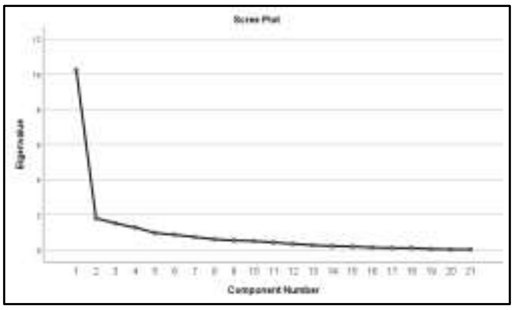

Figure 4.1 Scree plot of factor extraction results

In Figure 1 Scree Plot it can be seen that the number of factors that will be formed when the Initial Eigenvalues are greater than 1.00. 4 factors have values greater than 1. So these 4 factors can explain the 21 original variables.

4.8 Rotated Components Matrix

The extracted variables will be rotated because usually the placement of variables is not right or there are still variables that do not match the factors. The rotation process is carried out on variables that pass the MSA test. The component matrix can determine the contribution of variables to the factors formed.

Table 4.7 Rotated Component Matrix

Rotated Component Matrix[a]				
	Component			
	1	2	3	4
X1.1	**0.606**	0.330	0.200	0.193
X1.2	0.540	**0.561**	0.297	0.186
X1.3	0.397	**0.554**	0.080	0.262
X1.4	**0.669**	0.266	0.366	0.072
X2.1	0.080	**0.835**	0.167	0.128
X2.2	0.229	**0.748**	0.260	0.035
X2.3	0.512	**0.580**	0.107	0.085
X3.1	**0.758**	0.203	0.182	0.357
X3.2	**0.751**	0.148	0.149	0.223
X3.3	**0.768**	0.164	0.055	0.443
X3.4	**0.642**	0.049	0.361	0.046
X3.5	**0.679**	0.227	0.410	0.250
X4.1	**0.657**	0.370	0.216	-0.252
X4.2	**0.632**	0.466	-0.038	0.241
X4.3	**0.603**	0.510	0.083	0.305
X6.1	0.237	0.112	0.213	**0.793**

Rotated Component Matrix[a]				
	Component			
	1	2	3	4
X6.2	0.242	0.208	0.163	**0.851**
X7.1	0.113	0.428	**0.717**	0.164
X7.2	0.145	0.111	**0.866**	0.228
X7.3	0.462	-0.097	**0.728**	0.085
X7.4	0.188	0.364	**0.767**	0.041

Loading value identifies the correlation between variables and the factors formed. The higher the loading value means the closer the relationship between the variables and the factors. The table 4.7 illustrates that item X1.1 has the highest factor loading value of 0.606 on factor 1. Therefore, X1.1 is included in factor 1, and so are the rest of the items. It can be concluded as shown from the table above that factor number 1 named “planning factor”, consists of 10 (ten) items which are: lack of material storage space (X1.1), wasteful use of materials on site (X1.4), lack of competence in self-managed project implementers (X3.1), lack of competence of community facilitators (X3.2), lack of understanding of implementation guidelines and technical instructions (X3.3), failure to use personal protective equipment (X3.4), shortage of workers and delayed progress (X3.5), changes in project scope (X4.1), incomplete documents (X4.2) and design errors (X4.3). Meanwhile, factor number 2 named “material and equipment factors”, consists of 5 (five) items which are: delay in material delivery (X1.2), inappropriate quality and volume of materials (X1.3), insufficient quantity of equipment (X2.1), equipment breakdown (X2.2), equipment not suitable for site conditions (X2.3). Factor number 3 named “management factors”, consists of 4 (four) items which are: changes in leadership like community/organizations/institutions (X7.1), ineffective project supervision (X7.2), misuse of funds inconsistent with the planning (X7.3), delays in payment or disbursement of funds (X7.4). Furthermore, factor number 4 named “field condition factors”, consists of 2 (two) items which are: community resistance or opposition (X6.1), land acquisition issues (X6.2).

4.9 Dominant Risk Factors

a. Planning factors

Planning factors are factors formed from several sub-factors derived from the results of factor analysis. These factors have the highest variance value of 48.741%, which means that this factor is the factor that has the greatest or most dominant influence compared to other factors. This factor has 10 sub-factors, namely lack of material storage, wasteful use of materials in the field, lack of competence of self-management implementers, lack of competence of community assistants, lack of understanding of implementation instructions and technical instructions, non-use of personal protective equipment, shortage of workers and delayed progress, changes in the scope of work, incomplete documents (RAB, DED, RKS and other documents) and design errors. The variable that has the highest loading factor value is the lack of understanding of the implementation instructions and technical instructions with a factor loading value of 0.768. Understanding the implementation and technical instructions is essential, as they serve as guidelines to ensure that work is carried out in accordance with established standards. A lack of understanding in this regard can adversely affect the progress and success of the project. To address this, it is crucial to ensure that the implementation and technical instructions are prepared in a clear, detailed, and easily understandable manner. Additionally, providing socialization and training for self-management implementers on the relevant guidelines and instructions is essential to ensure effective project execution.

b. Material and Equipment Factors

Material and equipment factors are factors formed from several sub-factors derived from the results of factor analysis. These factors have the highest variance value of 8.582%. This factor has 5 sub-factors, namely delay in the delivery of materials, inappropriate material quality and volume, the number of equipment that does not meet the needs, work equipment malfunctions and equipment is not suitable for the working conditions. The variable that has the highest loading factor value is the amount of equipment that does not meet the needs with a loading factor value of 0.835. Calculation of material and equipment needs in accordance with the required amount will help minimize the risk of equipment shortages, avoid wasting resources, and ensure smooth project implementation.

c. Management Factors

Management factors are factors formed from several sub-factors derived from the results of factor analysis. These factors have the highest variance value of 7.208%. This factor has 4 sub-factors, namely changes in management (agencies/institutions/community organizations), work supervision processes that are not going well, utilization of funds that are not in accordance with planning and delays in payment/disbursement. The variable that has the highest factor loading value is the process of supervising work that is not going well with a loading factor value of 0.866. Good supervision can minimize errors that may occur. Therefore, a clear supervision plan is needed from the beginning of the work and performance indicators that must be met at each stage of the work and ensure that supervision is carried out regularly and on time.

d. Social Factors

Social factors are factors formed from several sub-factors derived from the results of factor analysis. These factors have the highest variance value of 6.063%. This factor has 2 sub-factors, namely rejection from the surrounding community and land acquisition. The variable that has the highest factor loading value is land acquisition with a factor loading value of 0.851. Land used for Environmental Scale Infrastructure Works needs to be confirmed to have a clear and clean status to prevent future claims and or disputes. So it is necessary to survey, confirm and record the status of land ownership and land documents that will be used for Environmental Scale Infrastructure Works activities at the planning stage.

V. CONSLUCION

There are four dominant risk factors affecting Environmental Scale Infrastructure Works in Palu City, the four factors are: 1) planning factors; 2) material and equipment factors; 3) management factors; 4) social factors, the amount of influence generated from all these factors reaches 70.594%, while the remaining 29.406% is influenced by other factors whose influence is not significant, this is obtained from the factor analysis test. From the results of this study, it was obtained that the highest influential factor was planning on *S*elf-managed Environmental Scale Infrastructure Project in Palu City with the highest Variance value of 48.741%. The response that must be done for the most dominant risk in this study is to pay attention to the planning stage. Good planning is needed for the success of a project. Planning must be made carefully and completely. In the planning stage, it is mandatory to make a project plan, do a job breakdown, make a workflow diagram, make clear guidelines and implementation instructions, prepare a schedule, collect resources, plan the use of PPE and identify risks.

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