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Multivariate Statistical Approach: Factor Analysis of Scabies Incidence in the Working Area of Bea Muring Health Center

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ABSTRACT

This study aims to demonstrate the application of factor analysis as one of the multivariate statistical methods in processing epidemiological data. Factor analysis is employed to reduce a set of correlated variables into simpler factors, thereby enabling more efficient identification of inter-variable relationship patterns. The data were obtained from surveys conducted within communities experiencing specific epidemiological cases, and were subsequently analyzed using validity testing, reliability testing, the Kaiser-Meyer-Olkin (KMO) measure, and Bartlett's Test of Sphericity as prerequisites for analysis. The results indicate that out of the initial 19 variables, 15 met the criteria and were reduced into three main factors, explaining a total variance of 74.79%. Factor 1 accounted for 44.45% of the variance, Factor 2 for 18.08%, and Factor 3 for 12.25%. These findings highlight the effectiveness of factor analysis in reducing the dimensionality of epidemiological data while identifying dominant factors influencing the observed phenomenon. In conclusion, this study demonstrates the potential of factor analysis as a relevant multivariate statistical method for handling complex data in public health as well as other applied fields.

INTRODUCTION

Life is inevitably inseparable from various disease cases. One of the common diseases is scabies. Scabies is a skin disease characterized by the appearance of rashes resembling pimples, scaling, and itching. According to the Ministry of Health of the Republic of Indonesia (Depkes RI), the prevalence of scabies in Indonesia, based on data from primary health centers (puskesmas) across the country in 2018, ranged from 5.6% to 12.95%, ranking third among the twelve most common skin diseases. Indonesia's tropical climate serves as a major contributing factor to the incidence of scabies [1]. Recently, scabies outbreaks have been reported in East Manggarai Regency, specifically in the working area of the Bea Muring Public Health Center, South Lamba Leda Subdistrict. This condition has persisted since January 2023, with residents frequently complaining of itching and skin rashes. Almost every day, numerous patients visit the health center with similar complaints [2], [3].

Scabies not only affects individuals physically but also has broader social and public health implications. Persistent itching and discomfort can disrupt daily activities, decrease productivity, and lead to secondary infections due to continuous scratching. In densely populated or resource-limited areas, such as rural communities in East Nusa Tenggara, scabies transmission tends to spread rapidly because of close interpersonal contact, inadequate sanitation, and limited access to clean water. Moreover, the lack of awareness and delayed treatment often exacerbate the disease burden, causing repeated outbreaks within households and communities. These conditions highlight the importance of conducting analytical studies to identify the dominant factors influencing the incidence of scabies, thereby enabling the design of effective and targeted intervention strategies.

Several studies have revealed that scabies incidence is influenced by multiple factors. The main factors associated with scabies include knowledge, attitudes, and lighting [4], [5]. Other contributing factors consist of economic level, sanitation, water availability, personal hygiene, and nutritional needs [6].

One of the methods employed to further investigate the determinants of scabies incidence is factor analysis [7]. Factor analysis is a statistical method used to reduce or summarise several independent variables into fewer underlying variables [8], [9]. In other words, factor analysis seeks to identify interrelationships among independent variables, thereby forming one or more groups of variables smaller than the original set. Furthermore, explain that factor analysis is a multivariate technique designed to observe and analyze phenomena to identify patterns. The numerous unobserved variables identified in the process are referred to as factors [10].

In a study conducted, factor analysis was applied to identify the determinants of dengue fever (DF) in North Maluku Province using Principal Component Analysis (PCA) [11]. The findings indicated that among all predictors, one main predictor component emerged, consisting of variables such as the non-working population, medical personnel, vulnerable-age population, working-age population, villages with health facilities, and healthcare services [12], [13]. The study results identified two factors: the first factor comprised three variables, while the second factor comprised two variables [14], [15].

This study presents a significant novelty (state of the art) by applying factor analysis to identify the main variables that simultaneously influence the incidence of scabies in the working area of Bea Muring Community Health Center. This approach provides a scientific contribution by reducing various influencing factors into several key components, allowing the results to serve as a foundation for developing more efficient prevention and control strategies [16]. Moreover, this research strengthens the application of multivariate statistical methods in the field of public health at the regional level, which has rarely been conducted comprehensively in East Nusa Tenggara.

METHODS

Data source

The types of data employed in this study consist of primary and secondary data. Primary data were obtained through the distribution of questionnaires to respondents diagnosed with scabies in the working area of the Bea Muring Public Health Center. Meanwhile, secondary data were utilized to determine the number of respondents to be studied, as obtained from the Bea Muring Public Health Center records.

Population and Sample

The sampling technique employed in this study is total sampling. Total sampling is a technique in which the sample size is equal to the population size [17]. Therefore, the number of samples in this study is 102 individuals [18], [19].

Research Variables

Factor analysis is one of the interdependence methods of analysis, in which variables cannot be distinguished as independent or dependent [20]. The variables used in this study are as follows:

Table 1. List of Indicators Causing Scabies

Variable	Statement
X_1	Scabies is a skin disease that affects the skin.
X_2	Symptoms of scabies include red spots that will heal within two days.
X_3	Keeping a distance from individuals with scabies is highly necessary.
X_4	Individuals with scabies should not be shunned or isolated.
X_5	Access to affordable and adequate healthcare services is well provided.
X_6	There are no difficulties regarding the cost of routine and effective medical treatment.
X_7	There are adequate facilities for waste disposal.
X_8	The water supply in my area is sufficient.
X_9	The water condition is clear and odorless.
X_{10}	Regularly sun-drying and replacing bed sheets is practised.
X_{11}	Clothes are dried under direct sunlight.
X_{12}	Clothes are ironed after drying before being worn.
X_{13}	Towels are dried under direct sunlight after being used.
X_{14}	Towels are shared alternately with other people.
X_{15}	Washing hands before and after meals is practiced.
X_{16}	Fingernails are kept clean by trimming them regularly.
X_{17}	Doors and windows are opened every morning.
X_{18}	Sunlight can enter the room.
X_{19}	The diet commonly consumed includes rice, meat, vegetables, and eggs.
X_{20}	Drinking eight glasses of water per day is practiced.
X_{21}	Bathing twice daily is practiced.
X_{22}	Garbage is disposed of in its proper place.

RESULTS AND DISCUSSION

Data Instrument Test

Validity testing originates from the term validity, which refers to the degree of accuracy and precision of a measurement instrument in performing its function. A validity test is used to assess whether a questionnaire is legitimate or valid [19], [21]. Meanwhile, a reliability test refers to the assessment of the consistency of a measurement instrument in determining the extent to which repeated measurements on the same subjects yield consistent results, provided that the measured aspects of the respondents remain unchanged [22], [23]. Reliability measurement is based on the value of Cronbach's Alpha (α), which is calculated as follows.

$$\alpha = \left[\frac{k}{k-1}\right]\left[1 - \frac{\Sigma S_j^2}{S_y^2}\right] \quad (1)$$

The following are the results of the validity and reliability tests on 30 respondents. This testing process was carried out to ensure that each questionnaire item accurately measures the intended construct and produces consistent results. The validity and reliability analyses were conducted using

SPSS version 2024, which generated output indicating that most questionnaire items met the validity criteria with Pearson correlation values above the r-table threshold (0.361), while a few items were found to be invalid and therefore excluded from further analysis.

Table 2. Validity Test Results

Variables	Pearson Correlation	R_{table}	Information
Item X_1	0,566	0,361	Valid
Item X_2	0,406	0,361	Valid
Item X_3	0,454	0,361	Valid
Item X_4	0,667	0,361	Valid
Item X_5	0,553	0,361	Valid
Item X_6	0,718	0,361	Invalid
Item X_7	0,156	0,361	Valid
Item X_8	0,507	0,361	Valid
Item X_9	0,618	0,361	Valid
Item X_{10}	0,679	0,361	Valid
Item X_{11}	0,600	0,361	Valid
Item X_{12}	0,502	0,361	Valid
Item X_{13}	0,538	0,361	Valid
Item X_{14}	0,544	0,361	Valid
Item X_{15}	0,616	0,361	Valid
Item X_{16}	0,174	0,361	Invalid
Item X_{17}	0,485	0,361	Valid
Item X_{18}	0,685	0,361	Valid
Item X_{19}	0,609	0,361	Valid
Item X_{20}	0,567	0,361	Valid
Item X_{21}	0,692	0,361	Valid
Item X_{22}	0,049	0,361	Invalid

Based on Table 2, the results of the validity test show that 19 items/statements were declared valid, as the calculated r values > r values at the 5% significance level. Subsequently, a re-test will be conducted, excluding the variables deemed invalid, until all variables meet the validity testing criteria.

Table 3. Reliability Test Results

Cronbach's Alpha	N of Items
0,888	19

From the reliability test results of the 19 items analyzed using SPSS 23, a Cronbach's Alpha value of 0.888 was obtained. This result, as shown in the SPSS 2024 output, indicates a high level of internal consistency among the questionnaire items. Since this value is greater than 0.6, it can be concluded that all tested items are reliable.

Correlation Test and Feasibility of a Variable

Before conducting factor extraction, it is necessary to test the correlation and feasibility of the variables to determine whether the data are appropriate for factor analysis. This step is performed using the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity [24], [25]. The results of these tests are presented in Table 4.

Table 4. KMO and Bartlett Test Values (1)

KMO		0,809
Bartlett's Test of Sphericity	Approx. Chi-Square	1467,543
	Df	171
	Sig.	0,000

From Table 4, it can be observed that the KMO value obtained was 0.809 and the Chi-square value was 1467.543 with a significance level of 0.000, indicating that the data are suitable and can be further analysed using factor analysis. These results were generated from the SPSS version 2024 output, which confirms that the sampling adequacy and correlation matrix meet the requirements for factor analysis. The use of the Chi-square value can also be found in a study entitled "Pearson Chi-Square Analysis of Factors Associated with Stunting Incidence" [15]. Furthermore, a KMO value greater than 0.8 indicates that the variables share a sufficient amount of common variance, suggesting that the data are highly appropriate for extraction of underlying factors. The significant Bartlett's Test result ($p < 0.05$) also supports this conclusion, confirming that the correlation matrix is not an identity matrix and that meaningful relationships exist among variables. Therefore, the dataset fulfills the fundamental assumptions for conducting factor analysis.

Table 5. MSA Value (1)

Variable	MSA Value
X_1	0.874
X_2	0.899
X_3	0.735
X_4	0,766
X_5	0,428
X_6	0.439
X_7	0,869
X_8	0,877
X_9	0,865
X_{10}	0,647
X_{11}	0,936
X_{12}	0,757
X_{13}	0,854
X_{14}	0,842
X_{15}	0,803
X_{16}	0,637
X_{17}	0,910
X_{18}	0,908
X_{19}	0,787

Furthermore, the Measure of Sampling Adequacy (MSA) values can be observed in Table 5, specifically in the anti-image matrices under the anti-image correlation section. The results, obtained from the SPSS version 2024 output, show that several variables had MSA values below 0.5, namely. X_5 and X_6. Consequently, repeated testing was carried out by excluding the variable X_5, as it had the lowest MSA value. Similarly, subsequent tests were conducted by removing variables with MSA values below 0.5. This process was repeated until all variables met the required criteria. After three iterations of testing, the results obtained were as follows.

Table 6. KMO and Bartlett Test Values (4)

KMO		0,872
Bartlett's Test of Sphericity	Approx. Chi-Square	1220,721
	Df	120
	Sig.	0,000

As shown in Table 6, the KMO value increased to 0.872 with a Chi-square value of 1220.721 and a significance level of 0.000, indicating that the data are suitable and can be further analysed using factor analysis. These results were obtained from the SPSS version 2024 output. The higher KMO value demonstrates that the intercorrelations among variables are stronger and more cohesive, suggesting that the dataset has achieved an optimal level of sampling adequacy for extracting meaningful and reliable factors.

Table 7. MSA Value (4)

Variable	**MSA Value**
X_1	0.874
X_2	0.898
X_3	0.824
X_4	0,892
X_7	0,889
X_8	0,873
X_9	0,863
X_{10}	0,671
X_{11}	0,936
X_{12}	0,763
X_{13}	0,862
X_{14}	0,854
X_{15}	0,796
X_{17}	0,914
X_{18}	0,904
X_{19}	0,862

Furthermore, Table 7 shows that the MSA values of all 16 variables were greater than 0.5, indicating that the data are suitable for further analysis. These results were obtained from the SPSS version 2024 output, which confirms that each variable has an adequate level of sampling adequacy. This means that all variables contribute meaningfully to the overall factor structure, allowing the subsequent factor extraction process to produce valid and interpretable results.

Factor Extraction

The values presented in the communalities table indicate that the existing variables can be explained by the extracted factors [26]. In other words, the greater the communality value, the stronger the relationship between the variable and the extracted factor, and the greater the extent to which the original variable characteristics are represented by the factor formed [27]. Based on the SPSS version 2024 output, most variables demonstrated high communality values, indicating that the

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extracted factors successfully captured a substantial portion of the variance contained in the original dataset. This result suggests that the factor extraction process was effective in identifying the dominant dimensions underlying the observed variables, providing a solid foundation for the subsequent rotation and interpretation stages.

Table 8. Communality (1)

Variabel	**Initial**	**Extraction**
X_1	1,000	0,617
X_2	1,000	0,866
X_3	1,000	0,904
X_4	1,000	0,731
X_7	1,000	0,689
X_8	1,000	0,829
X_9	1,000	0,800
X_{10}	1,000	0,118
X_{11}	1,000	0,742
X_{12}	1,000	0,774
X_{13}	1,000	0,636
X_{14}	1,000	0,615
X_{15}	1,000	0,667
X_{17}	1,000	0,678
X_{18}	1,000	0,841
X_{19}	1,000	0,774

As shown in Table 8, there are variables with Extraction values less than 0.5; such variables are considered not to meet the communality requirements and must therefore be excluded from the analysis. These results were obtained from the SPSS version 2024 output, which provides detailed information on the communality values for each variable. Consequently, the factor analysis procedure needs to be repeated from the beginning, excluding the variables that do not satisfy the communality criteria. Variables with low Extraction values indicate that a small proportion of their variance is explained by the extracted factors, suggesting weak relationships with the underlying factor structure. By removing these variables, the analysis can achieve a more stable and interpretable factor solution, ensuring that the retained variables contribute significantly to the overall model.

Table 9. KMO and Bartlett Test Values (5)

KMO		0,873
Bartlett's Test of Sphericity	Approx. Chi-Square	1218,775
	Df	105
	Sig.	0,000

As shown in Table 9, the Kaiser-Meyer-Olkin (KMO) value obtained was 0.873, while the Bartlett's Test of Sphericity produced a Chi-square value of 1218.775 with 105 degrees of freedom and a significance level of 0.000. These results were derived from the SPSS version 2024 output and indicate that the dataset meets the statistical assumptions required for factor analysis. The KMO value, which is greater than 0.8, demonstrates a high level of sampling adequacy, meaning that the variables share sufficient common variance to justify the application of factor analysis. In addition, the significant Bartlett's Test result ($p < 0.05$) confirms that the correlation matrix is not an identity matrix, signifying that meaningful relationships exist among the variables. Therefore, the data are considered appropriate for further extraction and interpretation of underlying factors.

Table 10. MSA Value (5)

Variable	MSA Value
X_1	0.875
X_2	0.897
X_3	0.826
X_4	0,896
X_7	0,888
X_8	0,873
X_9	0,864
X_{11}	0,936
X_{12}	0,761
X_{13}	0,862
X_{14}	0,853
X_{15}	0,794
X_{17}	0,915
X_{18}	0,904
X_{19}	0,862

After variable X_{10} was excluded, the KMO value increased to 0.873 with a significance level of 0.000, indicating that the requirements for the KMO and Bartlett's Test of Sphericity were fulfilled. Furthermore, Table 9 shows that the MSA values of the remaining fifteen variables were greater than 0.5. These results were obtained from the SPSS version 2024 output, confirming that the dataset meets the necessary assumptions for factor analysis. Thus, all fifteen variables can be further analyzed.

Table 10. Communality (2)

Variable	Initial	Extraction
X_1	1,000	0,621
X_2	1,000	0,865
X_3	1,000	0,905
X_4	1,000	0,731
X_7	1,000	0,691
X_8	1,000	0,827
X_9	1,000	0,800
X_{11}	1,000	0,741
X_{12}	1,000	0,796
X_{13}	1,000	0,644
X_{14}	1,000	0,613
X_{15}	1,000	0,690
X_{17}	1,000	0,678
X_{18}	1,000	0,841
X_{19}	1,000	0,775

Table 10. shows that the 15 tested variables met the communality requirements, as all had values greater than 0.5. These results were obtained from the SPSS version 2024 output, which provides

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detailed information on the communality values for each variable. Based on the communalities table, the greatest contribution was provided by the variable X_3 (contact with infected individuals) with a value of 0.905, meaning that 90.5% of the variance in the variable X_3 can be explained by the extracted factors. Conversely, the smallest contribution was provided by the variable X_{14} (handwashing) with a value of 0.613, indicating that 61.3% of its variance can be explained by the extracted factors. The next step is to examine the Total Variance Explained table, which illustrates the number of factors formed. To determine the extracted factors, the eigenvalues must be greater than 1. The high communality values across most variables indicate that the extracted factors adequately represent the original data structure, ensuring that little information is lost in the dimensionality reduction process. This suggests that the factor extraction model applied is robust and capable of summarizing the interrelationships among variables effectively.

Table 11. Extraction results using the principal component method

Component	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**		
	Total	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	6,668	44,450	44,450	6,668	44,450	44,450
2	2,713	18,085	62,535	2,713	18,085	62,535
3	1,838	12,257	74,792	1,838	12,257	74,792
4	0,762	5,081	83,867			
5	0,599	3,994	87,320			
6	0,518	3,453	89,626			
7	0,346	2,306	91,776			
8	0,322	2,149	93,513			
9	0,261	1,738	95,061			
10	0,232	1,548	96,588			
11	0,229	1,527	97,682			
12	0,164	1,094	98,746			
13	0,160	1,065	99,474			
14	0,109	0,728	100,000			
15	0,079	0,526				

From Table 11. It is shown that three components have eigenvalues greater than 1, namely $\lambda_1 = 6.668$, $\lambda_2 = 2.713$, and $\lambda_3 = 1.838$. These results were obtained from the SPSS version 2024 output, which provides detailed information on the eigenvalues and variance explained for each extracted component. Based on the criterion for determining the number of factors, three factors were extracted. These factors are used to explain the 15 variables. The eigenvalue of Component 1 is 6.668 (>1), thus forming Factor 1, which explains 44.450% of the variance. The eigenvalue of Component 2 is 2.713 (>1), thus forming Factor 2, which explains 18.085% of the variance. Meanwhile, the eigenvalue of Component 3 is 1.838 (>1), thus forming Factor 3, which explains 12.257% of the variance. The results of this analysis can also be illustrated using a scree plot. A scree plot is a graphical representation of eigenvalues against factors/components, and the number of reduced factors can be determined from the plot. The cumulative variance of 74.792% indicates that these three extracted factors collectively explain a substantial portion of the total variance, demonstrating that the model effectively summarizes the information contained in the original dataset.

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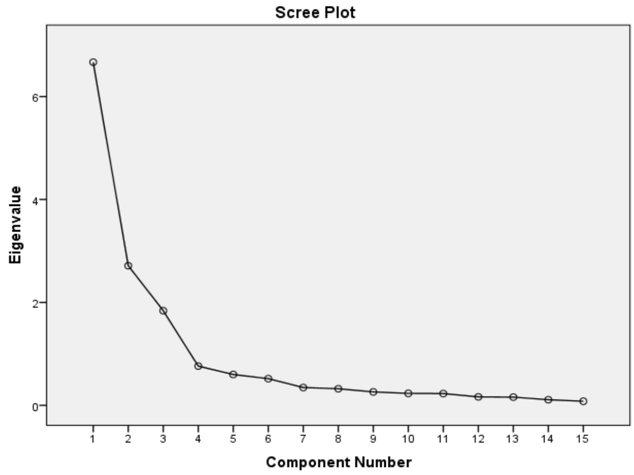

Figure 1. Sree Plot Graph

Factor Rotation

After determining the number of factors formed from the extraction process, the next step is to identify the relationship between each variable and the extracted factors. This relationship is expressed through the factor loading values, which indicate the strength of correlation between variables and factors [28], [29]. The factor loading results before rotation are presented in Table 12.

Table 12. Factor Loading Components

Variables	Component		
	1	2	3
X_1	0,677	-0,404	-0,013
X_2	0,780	-0,502	-0,064
X_3	0,773	0,506	-0,227
X_4	0,612	0,508	-0,314
X_7	0,573	-0,558	-0,226
X_8	0,720	-0,538	-0,137
X_9	0,763	0,418	-0,206
X_{11}	0,815	0,218	0,173
X_{12}	0,426	0,194	0,759
X_{13}	0,536	0,164	0,574
X_{14}	0,649	0,315	-0,305
X_{15}	0,431	0,250	0,665
X_{17}	0,704	-0,398	0,155
X_{18}	0,777	-0,487	0,010
X_{19}	0,601	0,581	-0,276

Factor loading represents the correlation between a variable and a factor, where ideally each variable strongly correlates with only one factor. A strong correlation is indicated when the factor loading value is greater than 0.50. The table above presents the factor loading components before rotation, making it difficult to determine which variables belong to which factors. Table 12 was obtained from the SPSS version 2024 output, which provides detailed information on the unrotated component matrix. Therefore, to obtain a simpler and more interpretable factor structure, a rotation of the factor loadings in Table 12 was performed using the varimax rotation method.

Table 13. Factor Loading Components After Rotation

Variabel	Component		
	1	2	3
X_1	**0,756**	0,167	0,151
X_2	**0,902**	0,190	0,122
X_3	0,184	**0,911**	0,205
X_4	0,081	**0,849**	0,066
X_7	**0,818**	0,093	- 0,114
X_8	**0,895**	0,161	0,026
X_9	0,238	**0,839**	0,199
X_{11}	0,379	**0,578**	0,514
X_{12}	0,072	0,067	**0,887**
X_{13}	0,187	0,196	**0,755**
X_{14}	0,245	**0,743**	0,044
X_{15}	0,044	0,147	**0,817**
X_{17}	**0,752**	0,115	0,314
X_{18}	**0,882**	0,166	0,191
X_{19}	0,017	**0,873**	0,113

From Table 13, it is evident that several factor loadings show very high correlations with only one component. These results were obtained from the SPSS version 2024 output, which presents the rotated component matrix after applying the varimax rotation method. The results of this rotation allow the determination of which variables are grouped under Factor 1, Factor 2, and Factor 3.

Interpretation of Factors

Thus, from 18 variables, 3 factors can be formed, each of which can be interpreted as follows. These factors represent the main dimensions influencing the incidence of scabies.

Table 14. Interpretation of Factors

Variabel	Factors	Eigen Values	Loading Factor	Variance (%)	Cumulative (%)
X_1	Knowledge, water, and nutrition factors	6,668	0,756	44,450	44,450
X_2			0,902		
X_7			0,818		
X_8			0,895		
X_{17}			0,752		
X_{18}			0,882		
X_3	Attitude and personal hygiene factors	2,713	0,911	18,085	62,535
X_4			0,849		
X_9			0,839		
X_{11}			0,578		
X_{14}			0,743		
X_{19}			0,873		
X_{12}	Factors of towel use and air sanitation	1,838	0,887	12,257	74,792
X_{13}			0,755		
X_{15}			0.817		

Therefore, the 15 variables were reduced into three factors. Factor 1 consists of variables X_1, X_2, X_7, X_8, X_{17}, and X_{18}. Factor 2 includes variables X_3, X_4, X_9, X_{11}, X_{14}, and X_{19}. Meanwhile, Factor 3 is composed of variables X_{12}, X_{13}, and X_{15}.

The factors influencing the incidence of scabies consist of 15 variables grouped into three factors. The first factor is knowledge, water, and nutrition, with an eigenvalue of 6.668 and a variance of 44.450%. The second factor is attitude and personal hygiene, with an eigenvalue of 2.713 and a variance of 18.085%. The third factor is towel usage and air sanitation, with an eigenvalue of 1.838 and a variance of 12.257%. Among these three factors, the most dominant factor influencing the incidence of scabies in the working area of the Bea Muring Public Health Center is knowledge, water, and nutrition. Therefore, it is recommended to provide community outreach regarding scabies prevention and to encourage proper nutrition intake. In addition, the quality of water should be considered to ensure its safety for consumption.

This study does not address all techniques within factor analysis. Future research is suggested to apply alternative methods for variable extraction and to further develop the analysis using discriminant analysis, path analysis, cluster analysis, and other multivariate techniques.

Research Implications

This study demonstrates that factor analysis can be effectively applied to epidemiological data, particularly in identifying the dominant factors influencing scabies incidence. The findings indicate that knowledge, water quality, and nutrition are the most significant determinants. This has important implications for public health interventions, as it emphasises the need to strengthen health education, improve access to clean water, and promote adequate nutritional intake to reduce the prevalence of scabies. Furthermore, the methodological implication is that factor analysis provides a robust statistical approach for reducing data dimensionality while maintaining interpretability, which can be applied to other public health and epidemiological studies.

In addition, these findings can serve as a basis for policymakers and health authorities to design targeted prevention programs that address the underlying determinants identified in this study. By focusing on community-based interventions and cross-sector collaboration between health, education, and sanitation agencies, sustainable improvements in disease control can be achieved. From an educational perspective, this study can also be used as a practical case study in multivariate statistics courses, allowing students to understand the application of factor analysis in real-world epidemiological contexts. Integrating such real data into the learning process can enhance students' analytical thinking, data interpretation skills, and their ability to apply statistical methods to solve actual public health problems.

CONCLUSIONS AND SUGGESTIONS

The results of the factor analysis successfully reduced 15 variables into three principal factors influencing the incidence of scabies in the working area of Bea Muring Community Health Center. The first factor, encompassing knowledge, water, and nutrition, was identified as the most dominant with an eigenvalue of 6.668, explaining 44.45% of the total variance. The second factor, attitude and personal hygiene, contributed 18.08%, while the third factor, towel usage and air sanitation, accounted for 12.25%, resulting in a cumulative variance explanation of 74.79%. These findings indicate that scabies incidence is determined not only by individual hygiene behaviour but also by the level of knowledge, water quality, and nutritional adequacy within the community. The study highlights that inadequate understanding of disease transmission, limited access to clean water, and poor nutritional conditions significantly contribute to the spread of scabies in rural tropical settings.

This research underscores the effectiveness of factor analysis as a multivariate statistical method for identifying dominant variables among complex epidemiological data. The findings contribute to public health practices by providing an empirical basis for designing targeted prevention strategies, including community education on hygiene, improvement of clean water facilities, and promotion of balanced nutrition. Moreover, the results reinforce the importance of integrating health education with environmental and socio-economic interventions in scabies control programs.

For Future Researchers: It is recommended to apply additional multivariate methods such as discriminant analysis, path analysis, or cluster analysis to provide deeper insights into the interrelationships among variables. Future studies may also expand to a larger population or different epidemiological contexts for broader generalization.

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