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Harvesting Insights: Factor Analysis of Agricultural Practices and Socio-Economic Variables

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Abstract

The agriculture of Western Odisha is vital to the region, but the state faces challenges and harbors immense potential for sustainable and inclusive growth. Using factor analysis, a powerful tool for disentangling complex relationships, the research identified three key drivers: a) Agricultural Financing & Support, b) Resources & Practices, and c) Economic Conditions & Insurance. These invisible strings orchestrate a significant portion of agricultural practices and their socio-economic consequences. By using a mixed-methods approach, combining quantitative data collected through a structured survey and qualitative analysis from 300 households the study sheds light on how access to financial resources and government programs fuels sustainable agriculture and well-being. Similarly, land availability, technology adoption, and strong social safety nets emerge as pillars of agricultural productivity. Finally, the study underlines the importance of stable economic conditions and comprehensive insurance coverage in empowering farmers and enabling them to weather the storms. Armed with these insights, policymakers, researchers, and practitioners can craft targeted interventions, optimize resource allocation, and steer Western Odisha's agriculture toward a sustainable and prosperous future.

Keywords: Factor Analysis; Agricultural Practices; Socio-Economic Factors; Agricultural Financing; Government Initiatives

Abbreviations

EFA: Exploratory Factor Analysis; CFA: Confirmatory Factor Analysis; SEM: Structural Equation Modelling; RMSEA: Root Mean Square Error of Approximation; BIC: Bayesian Information Criterion; TLI: Tucker-Lewis Index; KMO: Kaiser-Meyer-Olkin.

Introduction

In Western Odisha, agriculture is not just an economic activity but the very foundation of the region's socio-economic structure, providing livelihoods for a significant portion of the population. Despite facing numerous challenges, including unpredictable crop yields and disparities in accessing modern agricultural practices, it is an integral part of daily life and economic survival for many.

According to recent data, Odisha, a state in eastern India, is comprised of 30 districts and stands as the eighth largest in terms of land area, yet ranks eleventh in population. The state's economy predominantly relies on agriculture. However, Odisha grapples with significant disparities in regional development. Not all areas within the state reap equal benefits, owing to substantial economic, agricultural, and social constraints. Notably, non-governmental organizations (NGOs), leveraging their close ties with the farming community, have been instrumental in implementing decisions that harness enhanced information systems. Furthermore, they have successfully revitalized previously established technologies, contributing to more inclusive development Munda, et al. [1].

Understanding the complex factors that drive agricultural development is crucial in this context. These intertwined elements shape the trajectory of progress in Western Odisha's agriculture. Identifying and comprehending them is essential for formulating effective policies and targeted interventions. Munda, et al. [2].

This study embarks on a dedicated exploration of these underlying determinants, employing factor analysis as a powerful tool to systematically dissect the intricate relationships between various variables. The objective is to uncover the fundamental drivers propelling regional agricultural advancement.

The ultimate aim is to establish a solid sustainable and inclusive growth foundation. Through a profound understanding of the influencing factors, the goal is to cultivate a more resilient agricultural sector that ensures food security, and economic stability and fosters holistic development for the communities it serves. This study, therefore, represents a significant step towards laying the groundwork for a prosperous and sustainable future for Western Odisha.

Agriculture is pivotal in Western Odisha but faces challenges. Factor analysis helps uncover key drivers, revealing complex interplays between factors like technology, resources, and socio-economics.

Understanding these dynamics guides targeted policies, fostering sustainable and inclusive growth. This study seeks to catalyse positive change in the region's agricultural landscape.

Result and Discussion

Factor analysis, a statistical method extensively employed in social science research, aims to discover underlying factors or dimensions within a collection of observed variables. It offers researchers the means to investigate the connections between variables and reveal hidden constructs that might not be directly measurable. In the following section, we will examine pertinent literature concerning factor analysis and its utilization in various domains.

This classic paper by Cattell [3] introduces the screen test, a graphical method for determining the number of factors in factor analysis. The author explains the screen test procedure and provides guidelines for interpreting the scree plot to identify the elbow point where the eigenvalues start to level off. Floyd FJ, et al. [4]. This article examines the role of factor analysis in developing and refining clinical assessment instruments. The authors highlight the importance of factor analysis in establishing the construct validity and reliability of assessment measures. They discuss how factor analysis can inform item selection, scale construction, and refinement of psychological assessment tools. Velicer WF [5]. This seminal paper discusses a widely used method, known as the scree plot or eigenvalue-greater-than-one rule, for determining the number of factors to retain in exploratory factor analysis. The author proposes a simple graphical method based on the eigenvalues of the correlation matrix and provides guidelines for interpreting the scree plot Gorsuch RL [6].

This article focuses on the role of exploratory factor analysis in item analysis, which involves evaluating the psychometric properties of individual test items. The author discusses how factor analysis can help identify underlying constructs, assess item reliability and validity, and refine measurement instruments.

Stevens JP [7]. This comprehensive textbook provides an applied approach to multivariate statistics, including factor analysis.

It covers various factor extraction and rotation methods, as well as techniques for interpreting and reporting factor analysis results. The book includes examples and case studies from social science research to illustrate the practical application of factor analysis in different contexts. Hayton, JC, et al. [8].

Factor retention decisions in exploratory factor analysis: A tutorial on parallel analysis. Organizational Research Methods, 7(2), 191-205. This tutorial paper introduces the concept of parallel analysis as a method for determining the appropriate number of factors to retain in exploratory factor analysis. The authors explain the rationale behind the parallel analysis and provide step-by-step instructions for conducting the analysis. They also discuss the advantages of using parallel analysis over traditional methods such as eigenvalues or scree plots. Thompson B [9]. This book offers a comprehensive understanding of both exploratory and confirmatory factor analysis. It covers key concepts, such as factor extraction, rotation, model fit assessment, and reporting of results. The author provides clear explanations, practical examples, and guidelines for conducting factor analysis in different research contexts. Costello AB, et al. [10]. This article presents best practices and recommendations for conducting exploratory factor analysis (EFA). The authors discuss important considerations such as sample size, factor retention criteria, rotation methods, and interpretation of factor loadings. The article provides practical guidance to researchers on how to optimize their EFA procedures. Osborne, JW, et al. [11]. This article builds upon the earlier work by Costello AB, et al. [10] and provides additional recommendations for conducting exploratory factor analysis. The authors discuss important considerations, such as sample size, factor rotation, factor extraction methods, and factor interpretation. The article offers practical guidance for researchers to optimize their exploratory factor analysis procedures. Stevens JP [12].

Routledge. This textbook offers a practical and applied approach to multivariate analysis, including factor analysis. It covers the fundamental concepts, assumptions, and procedures of factor analysis, as well as advanced topics such as factor retention and interpretation. The book includes real-world examples and exercises to help readers grasp the concepts and apply factor analysis in their research. Green, SB, et al [13].

This article focuses on assessing dimensionality in factor analysis through internal consistency reliability measures, such as coefficient alpha and omega coefficients. The authors discuss the limitations of coefficient alpha in determining dimensionality and propose alternative measures. They provide guidelines for researchers to evaluate dimensionality using these reliability coefficients. Comrey AL, et al. [14]. This book provides a comprehensive introduction to factor analysis for beginners. It covers the basic concepts, procedures, and interpretation of factor analysis in a clear and accessible manner. The authors emphasize the practical application of factor analysis in psychological research and provide step-by-step instructions for conducting factor analysis using popular statistical software. Kim, HY [15].

While not specifically focused on factor analysis, this article discusses the assessment of normal distribution using skewness and kurtosis, which are relevant for factor analysis assumptions. The author explains how to interpret skewness and kurtosis values to determine the adequacy of the data for factor analysis. This information can be valuable for researchers conducting factor analysis in their studies.

These additional references further enhance the understanding of factor analysis and its applications. They provide researchers with valuable insights, practical guidance, and advanced techniques to optimize their use of factor analysis in their research studies. Gorsuch, RL [16]. This book offers a comprehensive overview of factor analysis, covering both exploratory and confirmatory factor analysis. It discusses various factor extraction methods, factor rotation techniques, and model fit indices for confirmatory factor analysis. The book also explores advanced topics, such as factor scores, multiple group factor analysis, and factor analysis with categorical data. Gorsuch RL [17]. Gorsuch RL [17] is a comprehensive textbook on the statistical technique of factor analysis, aimed at students and researchers in a variety of disciplines, including behavioural and social sciences, education, business, and economics.

The book covers the theoretical foundations of factor analysis, various methods for conducting factor analysis (such as principal components analysis, maximum likelihood methods, and exploratory factor analysis), interpreting factor results, and evaluating the quality of factor solutions. It also discusses advanced topics such as confirmatory factor analysis, structural equation modelling, and item response theory. Brown TA [18]. This book focuses on confirmatory factor analysis (CFA) and its application in applied research. It provides a step-by-step guide to conducting CFA, including model specification, identification, estimation, and evaluation. The author explains the key principles and issues in CFA and offers practical advice on analyzing and interpreting CFA results. Kline RB [19]. This comprehensive book covers both exploratory and confirmatory factor analysis as part of structural equation modeling (SEM). It provides detailed explanations of the underlying principles, steps involved in factor analysis, and interpretation of factor solutions. The book also discusses advanced topics such as model fit assessment and measurement invariance. Costello AB, et al. [10]. Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. This paper provides best practices and recommendations for conducting exploratory factor analysis. The authors discuss key considerations such as sample size, factor extraction methods, factor rotation techniques, and interpretation of factor loadings. They offer practical guidance to enhance the rigor and quality of factor analysis studies. Hayton, JC, et al. [20]. This tutorial article focuses on the use of parallel analysis as a method for determining the number of factors to retain in exploratory factor analysis. The authors explain the rationale behind the parallel analysis and provide step-by-step instructions for conducting it. They also discuss common issues and challenges related to factor retention decisions. Chen FF [21]. This article discusses the importance of measurement invariance in factor analysis and explores the sensitivity of goodness-of-fit indexes to violations of measurement invariance. The author provides insights into the impact of measurement non-invariance on factor analysis results and offers recommendations for addressing this issue in research studies. Suárez-Alvarez J, et al. [22]. This study demonstrates the use of factor analysis to examine changes in the factor structure of Raven's Progressive Matrices across different age groups. The authors apply confirmatory factor analysis to assess the invariance of the factor structure across ages and discuss the implications of the findings for intelligence testing. Fabrigar LR, et al. [23].

This tutorial article provides a step-by-step guide to conducting exploratory factor analysis (EFA) using parallel analysis and Velicer's MAP test to determine the number of factors to retain. The authors explain the procedures and provide practical examples to assist researchers in conducting robust and reliable EFA. O'Connor BP [24]. This article presents SPSS and SAS programs for conducting parallel analysis and Zwick WR, et al. [25]. This study compares five commonly used methods for determining the number of components to retain in exploratory factor analysis. The authors evaluate the performance of these methods using simulation studies and provide recommendations for researchers in selecting the most appropriate method based on their data characteristics. Wang J [26].

Structural equation modeling: Applications using Mplus Wiley. This book focuses on the application of structural equation modeling (SEM), which includes confirmatory factor analysis, using the Mplus software. It covers the theoretical foundations of SEM, model specification, estimation, model fit evaluation, and advanced topics such as mediation and moderation analysis. The book includes examples and guidance for conducting SEM analyses in various research fields.

Hypothesis

Null Hypothesis: There is no statistically significant relationship between the observed variables related to agriculture and the underlying factors.
Alternative Hypothesis: There is a statistically significant relationship between the observed variables related to agriculture and the underlying factors.

Methodology

The research utilized a mixed-methods approach, combining quantitative data collection with qualitative analysis, to comprehensively examine the factors influencing agricultural practices and policies in Western Odisha. This dual methodology offered a well-rounded understanding of the research topic, allowing for both statistical analysis and nuanced insights from qualitative data.

Data Collection

Quantitative Data Collection: The primary data for this study was obtained through a structured survey conducted in Western Odisha. To ensure representative results, a multi-stage random sampling method was employed. The sample size of 300 households was determined using the Rao soft sample size calculator, considering a margin of error of 5%, a confidence level of 95%, a population size of 10,000, and a response distribution of 30%. The various indicators under consideration are "Tools for Ploughing, Rashtriya Krishi Vikas Yojana, Purpose for Loan, National Rural Employment Guarantee Scheme, Current Financial Condition, Occupation Minimum Support Price, Fertilizer National Food Security Mission, The main source of income, Soil Test, Irrigation Facility, Types of crops, Gramin Bhandarana Yojana, Land Acquisition Law, National Agricultural Insurance Scheme, Reason for the destruction of crops, Types of seed, Pradhan Mantri Fasal Bima Yojana, Source of income and Agricultural Technology Insurance Scheme".

Trained enumerators personally administered the questionnaire to selected households, maintaining confidentiality and obtaining informed consent.
1.1.1. Data Analysis: The data obtained was analyzed through JAMOVI (2.4.1) using appropriate statistical methods. Descriptive statistics summarized sample characteristics, while inferential statistics like correlation and regression were used to explore relationships and test hypotheses. Factor analysis identified the latent variables that underlie the correlation among various indicators under consideration.
Ethical Considerations: Ethical guidelines were strictly followed. Informed consent was obtained, and participant confidentiality was maintained. The research protocol and survey instruments received ethical review board approval (G).
Limitations: The study's limitations include its geographic specificity (Western Odisha) and potential response biases due to self-reported data. Mitigation efforts included rigorous sampling, data quality checks, and cross-referencing data from multiple sources.

Objectives of the Study:

To identify key determinants shaping agricultural practices and policies in Western Odisha.
To assess the influence of socio-economic factors (e.g.,

education, income, land ownership) on agricultural decisions and technology adoption.

To investigate the interrelationships among agricultural variables, such as crop selection, land management, credit access, and government interventions.

To formulate evidence-based policy recommendations tailored to the specific challenges and opportunities in Western Odisha.

To contribute new insights, data, and analysis to the existing body of knowledge on agricultural practices and policies.

Statistical Analysis and Findings:

The data obtained was analyzed through JAMOVI (2.4.1) software under MS-windows 10 environment. And the results are presented as follows: (Tables 1-7)

Column 1	Factor-1	Factor-2	Factor-3	Column 5
Indicators	Factor-1	Factor-2	Factor-3	Uniqueness
Tools for Ploughing	-0.792			0.44128
Rastriya Krishi Vikas Yojana	0.567			0.7346
Purpose for Loan	0.535			0.51726
National Rural Employment Guarantee Scheme	0.51	0.505		0.34221
Current Financial Condition	0.468	0.409		0.39378
Occupation	0.458			0.74104
Minimum Support Price	0.404			0.86345
Fertilizer	0.352			0.74746
National Food Security Mission	0.318			0.79322
The main source of income	0.309			0.90069
Soil Test	0.3			0.84076
Irrigation Facility		0.762		0.45872
Types of crops		-0.667	0.447	0.08098
Gramin Bhandarana Yojana		0.487		0.64274
Land Acquisition Law		0.392		0.79876
National Agricultural Insurance Scheme				0.88686
Reason for the destruction of crops			1.017	0.00601
Types of seed		-0.36	0.57	0.3855
Pradhan Mantri Fasal Bima Yojana			0.354	0.81039
Source of income				0.93392
Agricultural Technology Insurance Scheme				0.96542
Note. The 'Minimum residual' extraction method was used in combination with a 'noblemen' rotation and three factors were extracted.				

Table 1: Factor Loadings.
Note: The 'Minimum residual' extraction method was used in combination with a 'noblemen' rotation and three factors were extracted.

Factor 1: Strong loadings on "Tools for Ploughing," "Rastriya Krishi Vikas Yojana," "Purpose for Loan," and "National Rural Employment Guarantee Scheme." This factor may represent the factors related to financing and support mechanisms in agriculture, including agricultural tools, government schemes, and loan proposals and can be named as "Agricultural Financing and Support".

Factor 2: Strong loading on "Irrigation Facility" and moderate loadings on "Types of crops," "Gramin Bhandarana Yojana," and "Land Acquisition Law." This factor may represent the factors associated with agricultural resources and practices, such as irrigation facilities, specific crop types, storage schemes, and land acquisition regulations and can be named as "Agricultural Resources and Practices".

Factor 3: Strong loadings on "National Agricultural Insurance Scheme, "Reason for destruction crops", "Types of seed", and "Pradhan Mantri Fasal Bima Yojana". 'This factor may represent the factors related to the economic condition of individuals involved in agriculture, crop insurance schemes, and the impact of factors like crop destruction and seed types.This factor can be named as "Economic Conditions and Insurance".

Summary	Column 1	Column 2	Column 3
Factor	SS Loadings	% of Variance	Cumulative %
1	2.92	13.9	13.9
2	2.41	11.5	25.4
3	2.38	11.3	36.7

Table 2: Factor summary.

In Table 2 the factor analysis revealed three distinct factors, collectively accounting for 36.7% of the total variance in the observed variables.

Factor 1: This factor is the most prominent and explains the largest proportion of variance, totaling 13.9%. It holds a significant influence on the analysis.

Factor 2: Contributes an additional 11.5% to the variance, resulting in a cumulative explained variance of 25.4% when combined with Factor 1.

Factor 3: Accounts for an additional 11.3% of the variance, leading to a cumulative explained variance of 36.7% when combined with Factors 1 and 2.

These factors collectively shed light on the underlying structures within the data and provide insights into the key drivers influencing agricultural practices and policies in the study area.

Inter-Factor Correlations	Column 1	Column 2	Column 3
Inter-Factor Correlations	Factor-1	Factor-2	Factor-3
1	—	0.237	-0.486
2		—	-0.3
3			—

Table 3: Inter-Factor Correlation.

Table 3 provided inter-factor correlations offer insights into the relationships among the three factors resulting from the factor analysis:

Factor 1 and Factor 2: A positive correlation of 0.237 indicates that higher scores on Factor 1 tend to be associated with higher scores on Factor 2. This suggests some degree of similarity or co-occurrence between these two factors.

Factor 1 and Factor 3: A negative correlation of -0.486 suggests an inverse relationship between Factor 1 and Factor 3. This means that higher scores on Factor 1 are associated with lower scores on Factor 3, and vice versa.

Factor 2 and Factor 3: A negative correlation of -0.300 indicates an inverse relationship between Factor 2 and Factor 3. Higher scores on Factor 2 tend to be associated with lower scores on Factor 3, and vice versa.

These correlations provide valuable insights into the associations and interactions between the factors derived from the factor analysis. The positive and negative correlations indicate varying degrees of similarity or dissimilarity between the factors, contributing to a comprehensive understanding of the underlying structures within the data.

	RMSEA 90% CI				Model Test		
RMSEA	Lower	Upper	TAG	BIC	χ^2	Df	p
0.0553	0.0458	0.065	0.9	-568	288	150	< .001

Table 4: Model Fit Measure.

Table 4 Based on the model fit measures provided, the factor analysis model demonstrates a reasonably good fit for the data:

RMSEA (Root Mean Square Error of Approximation): The RMSEA value of 0.0553 indicates a relatively small average discrepancy between the observed data and the model's predictions. The 90% confidence interval for RMSEA (0.0458 to 0.0651) suggests a range of plausible values for the population RMSEA.

TLI (Tucker-Lewis Index): With a value of 0.903, the TLI indicates that the factor analysis model has a relatively good fit compared to a baseline model. Values closer to 1 indicate a better fit, and a TLI of 0.903 suggests a reasonably good fit.

BIC (Bayesian Information Criterion): The BIC value of -568 takes into account both model fit and complexity. A lower BIC value suggests a better balance between fit and parsimony. In this case, the negative BIC value indicates a good fit relative to the model's complexity.

χ^2 (Chi-Square) and **df (degrees of freedom):** The χ^2 value of 288 with 150 degrees of freedom indicates a relatively good fit of the factor analysis model. A smaller χ^2 value relative to the degrees of freedom suggests a better fit.

p-value: The p-value associated with the χ^2 test is less than 0.001, indicating that the model fit is statistically significant. Overall, these measures collectively indicate that the factor analysis model provides a reasonably good fit for the data, supporting its validity and reliability in explaining the underlying structures within the dataset.

χ^2	df	P
2213	210	< .001

Table 5: Bartlett's Test of Sphericity.

In Table 5 Bartlett's Test of Sphericity yielded highly significant results (χ^2 = 2213, df = 210, p < 0.001), indicating that the variables in the factor analysis model are significantly correlated. This supports the suitability of factor analysis for examining the relationships among the variables, as the observed correlation matrix deviates significantly from an identity matrix.

KMO Measure of Sampling Adequacy	MSA
Overall	0.826
Types of seed	0.906
Occupation	0.859
The main source of income	0.872
Source of income	0.639
Tools for Ploughing	0.817
Rastriya Krishi Vikas Yojana	0.827
Gramin Bhandarana Yojana	0.935
National Food Security Mission	0.914
National Agricultural Insurance Scheme	0.899
Agricultural Technology Insurance Scheme	0.794
Pradhan Mantri Fasal Bima Yojana	0.727
Minimum Support Price	0.845
Types of crops	0.769
Fertilizer	0.825
Irrigation Facility	0.417
Soil Test	0.89
Reason for the destruction of crops	0.717
Purpose for Loan	0.917
Current Financial Condition	0.923
National Rural Employment Guarantee Scheme	0.898
Land Acquisition Law	0.823

Table 6: KMO Measure of Sampling Adequacy.

The KMO (Kaiser-Meyer-Olkin) Measure of Sampling Adequacy values assess the suitability of the data for factor analysis. Here's a description of the MSA values for each variable:

Types of Seed: This variable has a high MSA value of 0.906, indicating that it is well-suited for factor analysis.

Occupation: With an MSA value of 0.859, this variable demonstrates good sampling adequacy for factor analysis.

Main Source of Income: The MSA value of 0.872 suggests that this variable is suitable for factor analysis.

Source of Income: This variable has a moderate MSA value of 0.639, indicating some limitations in its suitability for factor analysis.

Tools For Ploughing: With an MSA value of 0.817, this variable is considered suitable for inclusion in the factor analysis.

Rashtriya Krishi Vikas Yojana: This variable has an MSA value of 0.827, suggesting good sampling adequacy for factor analysis.

Gramin Bhandarana Yojana: With a very high MSA value of 0.935, this variable is well-suited for factor analysis.

National Food Security Mission: Similarly, this variable has a very high MSA value of 0.914, indicating its suitability for factor analysis.

National Agricultural Insurance Scheme: With an MSA value of 0.899, this variable demonstrates good sampling adequacy for factor analysis.

Agricultural Technology Insurance Scheme: This variable has an MSA value of 0.794, suggesting its suitability for inclusion in the factor analysis.

Pradhan Mantri Fasal Bima Yojana: With a moderate MSA value of 0.727, this variable may have some limitations for factor analysis.

Minimum Support Price: This variable has a good MSA value of 0.845, indicating its suitability for factor analysis.

Types of Crops: With a moderate MSA value of 0.769, this variable may have some limitations in its adequacy for factor analysis.

Fertilizer: This variable has an MSA value of 0.825, suggesting its suitability for inclusion in the factor analysis.

Irrigation Facility: The MSA value for this variable is relatively low at 0.417, indicating potential limitations in its suitability for factor analysis.

Soil Test: With an MSA value of 0.890, this variable is considered suitable for inclusion in the factor analysis.

Reason for the Destruction of Crops: This variable has a moderate MSA value of 0.717, suggesting potential limitations in its adequacy for factor analysis.

Purpose for Loan: With a very high MSA value of 0.917, this variable is well-suited for factor analysis.

Current Financial Condition: This variable has a very high MSA value of 0.923, indicating its suitability for factor analysis.

National Rural Employment Guarantee Scheme: With an MSA value of 0.898, this variable demonstrates good sampling adequacy for factor analysis.

Land Acquisition Law: This variable has an MSA value of 0.823, suggesting its suitability for inclusion in the factor analysis.

In, most of the variables included in the analysis demonstrate good to very high sampling adequacy, indicating their suitability for factor analysis. However, it's important to consider the variables with lower MSA values, such as Irrigation Facility, Source of income, Pradhan Mantri Fasal Bima Yojana, Types of crops, and Reason for the destruction of crops, as they may have some limitations in their adequacy for inclusion in the factor analysis.

Factor	Eigenvalue
1	5.18093
2	1.21492
3	0.6465
4	0.32667
5	0.23945
6	0.17938
7	0.12698
8	0.03109
9	0.00931
10	-0.03252
11	-0.07716
12	-0.10062
13	-0.13238
14	-0.18373
15	-0.20069
16	-0.2194
17	-0.2469
18	-0.29993
19	-0.33241
20	-0.39198
21	-0.55659

Table 7: Initial Eigenvalues.

The provided eigenvalues represent the amount of variance explained by each factor extracted in the factor analysis. Here's how you can interpret the eigenvalues:

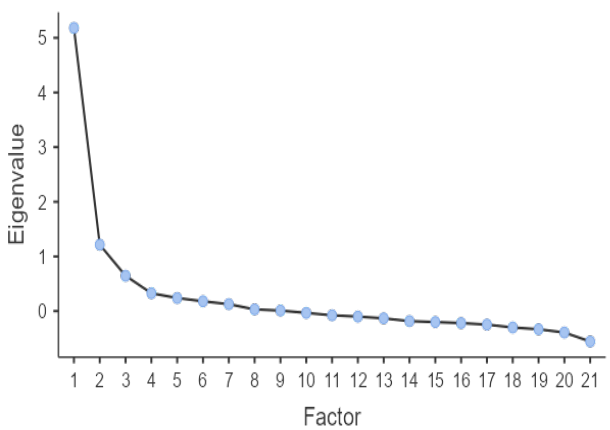
Factor 1: The eigenvalue is 5.18093, indicating that this factor explains a substantial amount of variance in the data.

Factor 2: The eigenvalue is 1.21492, suggesting that this factor explains a smaller amount of variance compared to Factor 1, but is still significant.

Factor 3: The eigenvalue is 0.6465, indicating that this factor explains a smaller amount of variance compared to Factors 1 and 2.

Factors 4 to 21: The eigenvalues for these factors progressively decrease. Negative eigenvalues suggest that these factors do not contribute meaningfully to explaining the variance in the data.

In factor analysis, it is common to consider factors with eigenvalues greater than 1 as significant and retain them for further interpretation. Based on the provided eigenvalues, it appears that the first three factors (Factor 1, Factor 2, and Factor 3) are the most important in explaining the variance in the data.



Screenplot 1: explaining the variance in the data**.**

The scree plot clearly indicates the identification of three factors, which collectively account for 36.7% of the variation in the dataset.

Conclusion

The factor analysis identified three key factors affecting agriculture in Western Odisha: Agricultural Financing and Support, Agricultural Resources and Practices, and Economic Condition Insurance.

Agricultural Financing and Support: Access to financial resources and government support is crucial for sustainable agriculture and socio-economic improvement. Policymakers should prioritize financial inclusion and targeted support.

Agricultural Resources and Practices: Land, technology, and social security are vital resources for productivity. Policymakers should promote technology adoption, sustainable land management, and robust social safety measures.

Economic Condition Insurance: Economic conditions and insurance are vital for farmers' resilience. Policymakers should focus on income diversification, improved insurance coverage, and social safety nets.

Understanding and addressing these factors will enable policymakers to promote sustainable agriculture, enhance productivity, and improve the well-being of farming communities in Western Odisha.

Policy Recommendation

To propel agriculture in Western Odisha, we recommend a multifaceted approach. Firstly, prioritize financial inclusivity and support through tailored financial products and literacy programs. Encourage technology adoption with targeted research and training programs. Strengthen extension services for timely information dissemination. Improve market access and infrastructure to reduce losses [27,28].

Advocate sustainable land management practices for resilience. Introduce comprehensive insurance schemes and income support. Foster research and innovation for region-specific solutions. Finally, ensure effective governance and policy implementation. Collaboration among stakeholders is paramount for success.

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