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# Impact of COVID-19 on Farmers: Insights from Factor Analysis

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***Authors' contributions***

*This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.*

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## ABSTRACT

The COVID-19 pandemic has inflicted profound disruptions on global economies, with significant repercussions for agriculture and rural communities. This study investigates the impact of COVID-

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19 on farmers through factor analysis, focusing on socio-economic dynamics and resilience in the agricultural sector. Data was collected from rural communities through focus group discussions, personal and key informant interviews in Chikkaballapur district, Karnataka, India, during the peak of the pandemic. Factor analysis was employed to identify underlying variables and explore the relationships among them. Results indicate that the pandemic has exacerbated existing challenges faced by smallholder farmers, disrupting agricultural activities and livelihoods. Factors such as education, family size, and farm size emerged as critical determinants of resilience, emphasizing the importance of socio-economic empowerment and resource access. Additionally, infrastructure and resource availability, represented by factors like water resources and service sector facilities, played pivotal roles in shaping agricultural outcomes. Insights from the principal component analysis (PCA) provide valuable guidance for policymakers and practitioners in devising targeted interventions to mitigate challenges and capitalize on opportunities in rural areas. By understanding the key factors driving socio-economic dynamics and agricultural productivity, stakeholders can foster sustainable development and resilience in agricultural communities amidst unprecedented global crises like COVID-19. The study underscores the urgent need for evidence-based strategies to address the multifaceted impacts of the pandemic, ensuring the well-being and resilience of farmers and rural communities in the face of uncertainty and adversity. Based on the findings, it is recommended that policymakers prioritize socio-economic empowerment and infrastructure development in rural areas to enhance resilience and sustainable development in agricultural communities, especially during global crises like the COVID-19 pandemic.

*Keywords: Agriculture; COVID-19; factor analysis; rural resilience; socio-economic impact.*

## 1. INTRODUCTION

The emergence of the COVID-19 pandemic in late December 2019 marked a pivotal moment in modern history, disrupting lives, economies, and ecosystems across the globe. This unprecedented health crisis, which swiftly spread across more than 227 countries and territories, has not only posed a threat to public health but has also significantly impacted various sectors of the economy, particularly agriculture. As Junuguru and Singh [1] metaphorically stated, the pandemic acted as fuel to an already burning global economic situation, intensifying existing challenges and creating new ones.

Originating in Wuhan, Hubei province, China, the novel infectious respiratory illness, officially named COVID-19 by the World Health Organization, has unleashed a wave of economic shockwaves. The disruption has been particularly profound in the agricultural sector and food supply chains, leading to a ripple effect that has affected livelihoods, human capital, and labour across the world [2,3].

Smallholder farmers, who form the backbone of many economies, have borne the brunt of the pandemic's economic fallout. The restrictions imposed to contain the virus, including mobility restrictions and social distancing measures, have severely constrained labour-intensive activities in fresh produce production. This has jeopardized the ability of poorer populations to earn income through their primary asset—physical labour [4,5]. Furthermore, sectors such as dairy farming, floriculture, fruit production, fisheries, and poultry farms have been particularly hard hit, with significant income losses and market disruptions [6].

While the pandemic has brought forth numerous challenges, it has also presented some unexpected environmental benefits [7]. Reduced human activity has led to a noticeable drop in carbon and nitrogen dioxide emissions, coal consumption, and pollution levels [8]. Examples such as the clear waters of the canals in Venice, Italy, where fishes play undisturbed, serve as stark reminders of the impact of reduced human intervention on the environment.

Given this backdrop, this paper seeks to address a pressing question: What has happened to agriculture and farmers over more than a year of living with COVID-19? By examining the challenges faced by the agricultural sector amidst the COVID-19 pandemic and lockdown measures, this research aims to shed light on the resilience of the agricultural sector, the adaptability of farmers, and the policy interventions required to ensure a more sustainable and resilient future. This paper primarily centers on utilizing factor analysis to streamline a collection of intricate variables, aiming to uncover the fundamental dimensions that clarify the connections among these various variables.

## 2. METHODOLOGY

The research was undertaken in the Chikkaballapur district of southern Karnataka throughout 2020-21, with the objective of evaluating how the COVID-19 pandemic influenced rural livelihoods. A sample size of 50 participants was chosen, comprising 25 individuals from Chintamani taluk and 5 from each of the other taluks due to traveling restrictions. Data gathering occurred during the height of the pandemic via face-to-face interviews.

Utilizing an ex-post-facto descriptive research approach, the study aimed to grasp the present perceptions, obstacles, and behaviours prevailing within rural communities amid the pandemic. This method, endeavours to discern the rationales behind an event post its occurrence. The selection of this design was justified for the study given its congruence with the research objectives, variables, sample size, and the phenomenon under scrutiny.

The research incorporated a range of independent (X1-X11) and dependent variables (Y1-Y5) to analyse the pandemic's impact on various socioeconomic aspects. Independent variables encompassed demographics, agricultural methods, and resource availability factors such as age, education, family size, farm size, income, number of farm vehicles, number of livestock, water availability, primary crops cultivated, health and sanitation provisions, and service sector amenities. Dependent variables represented alterations observed due to COVID-19 across economic domains, including income per acre, changes in cultivation area, adoption of agricultural technology, responses to market dynamics, and adjustments in farming management practices.

Data collection involved the use of a pretested structured interview schedule, meticulously designed to align with the study's objectives and variables. The schedule underwent pretesting in a location excluded from the main study to ensure reliability. Following the pretesting phase, necessary adjustments were made in consultation with experts and authorities to enhance the schedule's efficacy and relevance. The interview schedule included a combination of open-ended and closed-ended questions, providing flexibility during interviews and covering a wide range of topics pertinent to the study.

For this study, factor analysis was employed as the statistical method. Factor analysis is a technique used to elucidate variability among observed, correlated variables by positing a smaller number of unobserved variables termed factors. It categorizes akin variables into the same factor to unveil underlying constructs, relying solely on the data correlation matrix. The Kaiser-Meyer-Olkin (KMO) test was conducted to gauge the appropriateness of the data for factor analysis. Essentially, the KMO test assesses the adequacy of the sample size by measuring sampling adequacy for each variable within the model as well as for the entire model.

To ascertain the number of initial unrotated factors to be extracted, Kaiser's criterion and the Scree test were employed. Eigenvalues associated with each factor delineate the variance explained by those particular linear components. Coefficients below 0.4 were suppressed as per Kaiser [9], thereby excluding factor loadings with values under 0.4 from presentation.

In this study, the extraction method utilized principal component analysis, while the orthogonal rotation method employed varimax with Kaiser Normalization. This approach aids in simplifying the interpretation of factors by maximizing the variance of factor loadings.

In this study, orthogonal factor rotation was chosen over oblique rotation due to its propensity to yield solutions that are more straightforward to interpret and articulate. Among the methods associated with orthogonal rotation—varimax, quartimax, and equimax—the varimax method, pioneered by Kaiser [10] was employed. Varimax aims to reduce the number of variables with high loadings on each factor, enhancing interpretability. Varimax emphasizes maximizing the differences between squared pattern structure coefficients on a factor, focusing on a column perspective. It seeks to maximize the spread in loadings, resulting in higher loadings becoming even higher after rotation and lower loadings becoming even lower. In instances where the rotated component matrix reveals numerous significant cross-loading values, it is advisable to rerun the factor analysis. This rerun involves eliminating cross-loaded variables to ensure that each item loads distinctly onto only one component, thus enhancing the clarity of interpretation [11,12].

The communality of the $j^{th}$ variable refers to the proportion of variance in that variable explained by the 'm' common factors. Mathematically, it is expressed as $\sigma jj = h_j^2 + \psi_j$, where $\sigma_{jj}$ represents the variance of variable $X_j$ (the $j^{th}$ diagonal of $\Sigma$). The communality $h_j^2$ is the sum of squared loadings for $X_j$, denoted by $(\lambda\lambda')_{jj} = \lambda_{j1}^2 + \lambda_{j2}^2 + ... + \lambda_{jm}^2$, and it signifies the shared variance of $X_j$. On the other hand, $\psi_j$ represents the specific variance or uniqueness of $X_j$. This equation encapsulates both the common and unique variance components of the variable $X_j$ [13,14].

## 3. RESULTS AND DISCUSSION

This segment presents the outcomes derived from utilizing the statistical tool SPSS. Kaiser-Meyer-Olkin is employed to assess the data's adequacy for factor analysis, along with Bartlett’s test of Sphericity, correlation matrix, and principle component analysis, as suggested by Pett et al. [15], to ascertain the suitability of the dataset for conducting factor analysis.

Table 1 exhibits the correlation matrix, indicating adequate correlations to warrant the use of factor analysis. Notably, the correlation matrix reveals several items with inter-correlations exceeding 0.3 between variables, suggesting the appropriateness of the hypothesized factor model.

Table 2 displays that the Kaiser-Meyer-Olkin (KMO) statistic yields a value of 0.513, surpassing the threshold of 0.5, indicating sufficient sampling adequacy and thereby justifying the application of factor analysis. Bartlett’s test of Sphericity, utilized to assess the adequacy of the correlation matrix, yields high significance at $p < 0.001$, suggesting significant correlations among some variables. Specifically, the test value is 98.301 with a significance level below 0.0001, leading to the rejection of the hypothesis that the correlation matrix is an identity matrix, indicating that variables are not orthogonal. With a significant value below 0.05, it is indicated that a factor analysis may be valuable for the dataset.

Table 3 present the eigenvalues and total variance explained, respectively. Principal component analysis is employed as the extraction method for factor analysis in this study. Prior to extraction, eleven linear components are identified within the dataset. Following extraction and rotation, five distinct linear components emerge within the dataset, corresponding to eigenvalues greater than 1. These five factors collectively account for 68.114% of the total variance. It is recommended in Principal Component Analysis that retained factors should collectively explain at least 50% of the total variance. The outcome indicates that 68.11% of the common variance shared by eleven variables can be attributed to five factors, aligning well with the KMO value of 0.513, which signifies good suitability for factor analysis with the variables. This initial solution suggests that the final solution will not extract more than five factors. The first component (Age) explains 23.18% of the total variance with an eigenvalue of 2.55. The second component (Education) explains 35.77% variance with an eigenvalue of 1.385. The third component (Family size) explains 48.204% variance with an eigenvalue of 1.367. The fourth component (Farm size) explains 58.386% variance with an eigenvalue of 1.12. Finally, the fifth component (Income) explains 68.114% variance with an eigenvalue of 1.07.

Eigenvalues represent the amount of variance explained by each factor, with factors having higher eigenvalues considered more significant. In contrast, a scree plot visually represents the eigenvalues in descending order, helping to identify the point where the explained variance drops off, which aids in determining the optimal number of factors to retain. Using a scree plot is advantageous because it provides a clear visual cue for the "elbow" point, where the addition of more factors yields diminishing returns in explained variance. Fig. 1 depicts the Scree test, where a graph is plotted with eigenvalues on the y-axis against the eleven component numbers in their order of extraction on the x-axis. Initially, larger factors with higher eigenvalues are extracted, followed by smaller factors. The Scree plot serves to identify the number of factors to retain. In this case, the Scree plot indicates that there are five factors with eigenvalues greater than one, which collectively explain most of the total variability in the data. The remaining factors contribute only a minimal proportion of the variability and are considered less important.

Table 4 displays the factor loading, percentage of variance, and cumulative variance using principal component analysis, along with communality after extraction. Communality reflects the common variance in the data structure after

**Table 1. Correlation matrix**

| Variable | Age | Education | Family size | Farm size | Income | No. of farm vehicle | No. of farm animals | Water resources available | Crop growth | Health and sanitation | Service sector facilities |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Age | 1.000 | -0.227 | -0.211 | -0.113 | -0.134 | 0.039 | 0.026 | -0.218 | -0.053 | -0.174 | 0.047 |
| Education | -0.227 | 1.000 | 0.306 | 0.393 | 0.174 | 0.066 | -0.056 | -0.110 | -0.31 | 0.006 | -0.164 |
| Family size | -0.211 | 0.306 | 1.000 | 0.775 | 0.346 | 0.268 | -0.104 | 0.076 | 0.092 | -0.071 | -0.161 |
| Farm size | -0.113 | 0.393 | 0.775 | 1.000 | 0.459 | 0.334 | 0.024 | -0.049 | 0.095 | -0.103 | -0.098 |
| Income | -0.134 | 0.174 | 0.346 | 0.459 | 1.000 | 0.142 | -0.083 | -0.052 | 0.055 | 0.159 | -0.107 |
| No. of Farm vehicle | 0.039 | 0.066 | 0.268 | 0.334 | 0.142 | 1.000 | -0.091 | -0.079 | 0.140 | 0.046 | 0.000 |
| No.of farm animals | 0.026 | -0.056 | -0.104 | 0.024 | -0.083 | -0.091 | 1.000 | -0.017 | 0.048 | 0.180 | -0.132 |
| Water resources available | -0.218 | -0.110 | 0.076 | -0.049 | -0.052 | -0.079 | -0.017 | 1.000 | 0.036 | -0.057 | -0.245 |
| Crop growth | -0.053 | -0.031 | 0.092 | 0.095 | 0.055 | 0.140 | 0.048 | 0.036 | 1.000 | 0.207 | -0.061 |
| Health and sanitation | -0.174 | 0.006 | -0.071 | -0.103 | 0.159 | 0.046 | 0.180 | -0.057 | 0.207 | 1.000 | 0.149 |
| Service sector facililites | 0.047 | -0.164 | -0.161 | -0.098 | -0.107 | 0.000 | -0.132 | -0.245 | -0.061 | 0.149 | 1.000 |

**Table 2. KMO and Barlett's test**

| | |
|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy | 0.513 |
| Barlett's test of Sphericity | |
| Approx. Chi-square | 98.301 |
| Df | 55 |
| Significant | <0.001 |

**Table 3. Total variance explained**

| Component | Initial Eigen values | | | Extraction sums of squared loadings | | |
|---|---|---|---|---|---|---|
| | Total | % of variance | Cumulative % | Total | % of variance | Cumulative % |
| 1 | 2.550 | 23.186 | 23.186 | 2.550 | 23.186 | 23.186 |
| 2 | 1.385 | 12.589 | 35.775 | 1.385 | 12.589 | 35.775 |
| 3 | 1.367 | 12.429 | 48.204 | 1.367 | 12.429 | 48.204 |
| 4 | 1.120 | 10.182 | 58.386 | 1.120 | 10.182 | 58.386 |
| 5 | 1.070 | 09.728 | 68.114 | 1.070 | 09.728 | 68.114 |
| 6 | 0.833 | 07.571 | 75.685 | | | |
| 7 | 0.792 | 07.201 | 82.886 | | | |
| 8 | 0.726 | 06.597 | 89.483 | | | |
| 9 | 0.545 | 04.955 | 94.439 | | | |
| 10 | 0.450 | 04.093 | 98.532 | | | |
| 11 | 0.161 | 01.468 | 100.000 | | | |

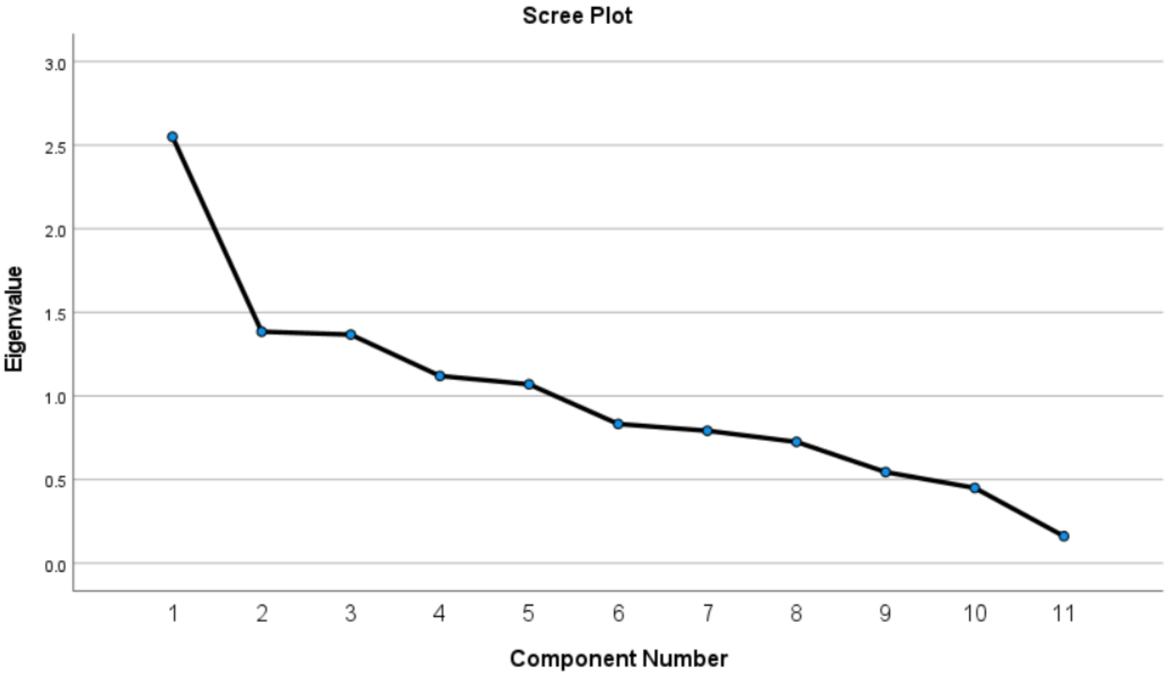


**Fig. 1. Scree plot**

factor extraction. Factor loading values indicate the relationship of each variable to the underlying factors, with variables having large loading values (> 0.40) being representative of the factor.

Factor 1 encompasses four variables: education, family size, farm size, and income, exhibiting correlations of 0.549, 0.846, 0.881, and 0.606 with factor 1, respectively. Factor 1 explains 23.186% of the total variance.

The principal component analysis (PCA) results offer valuable insights into the underlying structure of the dataset, shedding light on the

**Table 4. Communalities, Per cent of variance and cumulative using principal component analysis**

| Factors | Independent variable | Eigen value | Communalities ($h^2$) | Factor loading | % of variance | Cumulative % |
|---|---|---|---|---|---|---|
| I | Education | 1.000 | 0.578 | 0.549 | 23.186 | 23.186 |
| | Family size | 1.000 | 0.740 | 0.846 | | |
| | Farm size | 1.000 | 0.828 | 0.881 | | |
| | Income | 1.000 | 0.421 | 0.606 | | |
| II | Water resources available | 1.000 | 0.760 | -0.756 | 12.589 | 35.775 |
| | Service sector facilities | 1.000 | 0.678 | 0.627 | | |
| III | Crop growth | 1.000 | 0.613 | 0.539 | 12.429 | 48.204 |
| | Health and Sanitation | 1.000 | 0.766 | 0.831 | | |
| IV | Age | 1.000 | 0.739 | 0.558 | 10.182 | 58.386 |
| V | No of Farm vehicles | 1.000 | 0.570 | 0.000 | 09.728 | 68.114 |
| | No of Farm animals | 1.000 | 0.798 | -0.656 | | |

interrelationships among various variables. Each factor extracted from the analysis demonstrates equal eigenvalues of 1.000, indicating their equal contribution to explaining variance. Communalities (h2) further elucidate the extent to which individual variables contribute to the factors, with factors like Education, Family size, and Income displaying substantial communalities, implying a significant portion of their variance is captured by the extracted factors. Factor loadings reveal strong associations between certain variables and factors, such as Water resources available and Service sector facilities with Factor II, suggesting a distinct underlying dimension related to infrastructure and resource availability. Moreover, the cumulative percentage of variance steadily increases with each factor considered, reaching 68.114% after accounting for Factors I to V, demonstrating the cumulative explanatory power of the extracted factors in the dataset.

The implications of these findings extend to various stakeholders involved in rural development and agricultural policymaking. Understanding the key factors driving socio-economic dynamics and agricultural productivity is crucial for devising targeted interventions and policies aimed at improving rural livelihoods and fostering sustainable development especially during the times like COVID19 pandemic. Factors such as Education, Family size, and Farm size highlighted in the analysis underscore the importance of socio-economic empowerment and resource access in rural communities. Additionally, insights into infrastructure and resource availability, as captured by Factor II, can inform investment priorities and infrastructure development initiatives. By leveraging the findings of this PCA, policymakers and practitioners can design evidence-based strategies to address challenges and capitalize on opportunities in rural areas, ultimately contributing to enhanced well-being and resilience in agricultural communities.

## 4. CONCLUSION

The principal component analysis (PCA) conducted in this study has provided valuable insights into the multifaceted impact of the COVID-19 pandemic on agriculture and rural communities. The analysis of various socio-economic factors and their interrelationships has highlighted the challenges faced by farmers and the agricultural sector during the pandemic. Factors such as Education, Family size, and Farm size emerged as critical determinants of resilience, highlighting the importance of socio-economic empowerment and resource access in rural areas. Moreover, the findings underscore the significance of infrastructure and resource availability, with factors like Water resources available and Service sector facilities playing pivotal roles in shaping agricultural outcomes. By leveraging these insights, policymakers and practitioners can craft evidence-based interventions to mitigate challenges and capitalize on opportunities, ultimately fostering sustainable development and resilience in agricultural communities in the face of unprecedented global crises like COVID-19.

## DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that generative AI technologies such as Large Language Models, etc have been used during writing or editing of manuscripts. This explanation will include the name, version, model, and source of the generative AI technology and as well as all input prompts provided to the generative AI technology

**Details of the AI usage are given below:**

1. ChatGPT was used to find and correct grammar mistakes.

## CONSENT

As per international standard or university standard, respondents' written consent has been collected and preserved by the author(s).

## COMPETING INTERESTS

Authors have declared that no competing interests exist.

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