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ARTICLE

Understanding the Impact of Agriculture Insurance: Insights and Challenges of PMFY Scheme from Four States of India Using Pearson Correlation

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ABSTRACT

In India, agriculture and the allied sector is one of the foremost sectors but it is highly dependent on weather, which makes it highly susceptible to climate change risks. Thus, building resilience in the sector becomes imperative. This paper will dwell on ex-post strategy of mitigative measure, by focusing on agricultural insurance (AIn). Currently, PMFBY 2.0, which was rolled out to stabilize farmers' incomes against the increasing risks due to climate change and the SDGs. The review of the existing literature establishes a dire need for a comprehensive assessment of PMFBY on parameters such as awareness, satisfaction, and transparency. Thus, the present study attempts to fill this gap by measuring the perceived impact (PI) of PMFBY on three variables: awareness, satisfaction, and transparency. The study uses a sequential exploratory mixed-method research design, utilizing qualitative methods and quantitative methods. It uses 15 in-depth interviews and a questionnaire with dichotomous and matrix Likert scale questions to understand variables' effects on scheme performance in four states and their districts. The analysis

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was done using Pearson correlation to measure the linear correlation of PI of farmers on these variables. The results highlight multicollinearity among the factors, which indicates that PI has a positive relationship with the selected variables. Thus, provides a policy dimension to improve the effectiveness of the scheme through three interconnected variables. The study addresses the issue of the comprehensive assessment of PI on the PMFBY and provides a way forward for policymakers to create resilient policies in the sector.

Keywords: Pradhan Mantri Fasal Bima Yojana (PMFBY); Crop Insurance; Pearson Coefficient; Agriculture Impact; Sustainable Development Goals (SDGs); Farmers; Agriculture Resilience

1. Introduction

In India, the agriculture sector's dependency on the weather is quite high. The sector plays a vital role in ensuring its sustainable growth and economic progress It accounts for 18.6% of the country's GDP and meets the nutritional needs of 55% of the population [1]. As India has been primarily an agrarian economy, the sector is a major contributor to India's economic development. But it is heavily dependent upon weather (climatic) factors. Due to the reliance on the weather condition the sector is largely affected byclimate risk; managing such risk is a critical factor. The agriculture sector is beset with production risk due to its likely dependency on climatic conditions. Thus, climate change vulnerability in the agriculture sector includes various risks such as floods, droughts, cyclones, pest attacks, irregularity of supply chains, etc. [2]. As weather variables accentuate the agriculture risk, mitigating such complex and cumbersome risks has become a challenge for the government, not only in India but across the globe. There are varieties of mitigative measures undertaken, which can be broadly categoried as ex-ante and ex-post measures. The ex-ante measures aim towards income equalization whereas ex-post measures look towards production resolution. The first includes the mixed-farming practices, precision farming, agriculture insurance (AIn), seeding technology, and income diversification. Whereas the second includes migration, borrowing, sale of assets, etc. [3]. The former is more positive in approach and helps in the resilience of the agriculture sector. Thus, addressing the challenges faced by the agriculture sector from climate change is essential to improve the resilience of the sector. So, the basic objective of AIn schemes is to bolster the resilience and sustainability of farmers [4].

The United Nations Office for Disaster Risk Reduction (UNISDR) (2018) reported that nations affected by disasters incurred direct economic losses amounting to US$ 2,908 billion from 1998 to 2017 [5]. Out of the total loss 70% was attributed to climate-related events. The effects of climate change on the agricultural industry have been increasingly obvious in recent years. The Government of India's economic survey (2018) projected that the annual loss attributable to the detrimental impacts of climate change was between US$ 9 billion and US$ 10 billion. Malhi, Kaur and Yadav further suggest that in India, the increase in temperature, with double the concentration of CO2 and the extension of heat waves, will adversely affect the agriculture sector [6]. There is a fluctuating effect of climate change from 2000–01 to 2016–17 on the cropped areas in India, but still, the pattern suggests that there should be strong and resilient strategies for mitigating such impacts in India (**Figure 1**).

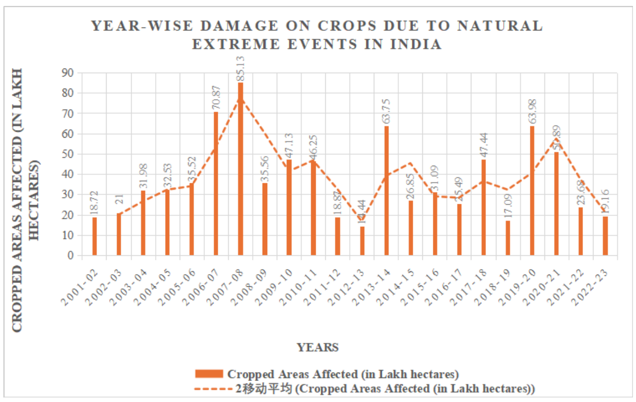

Figure 1. Year-wise damage to crops due to natural extreme events in India (2000–01 to 2022–23).

Note: For 2019–20 as of 31.12.2019; 2. For 2020–21 as of 02.12.2020; 3. For 2021–22 as of 31.12.2021; 4. For 2022–23 as of 25.11.2022

Source: National Statistical Office. (2024). *EnviStats-India 2024: Environment statistics* (Chapter 4, p. 198). Ministry of Statistics & Programme Implementation, Government of India. Retrieved July 21, 2024, from https://www.mospi.gov.in/sites/default/files/reports_and_publication/statistical_publication/EnviStats/Complete_ES1_2024.pdf

As, AIn provides farmers with financial compensation for projected crop losses caused by uncontrollable natural phenomena such as fire, weather disasters, floods, pests, and diseases. Its expansion is propelled by the growing commercialisation of agriculture, global trade, foreign direct investment, and the introduction of innovative insurance products. It plays a crucial role in stabilising agricultural income and alleviating poverty, which are key objectives of Sustainable Development Goals (SDG 1). Similarly, it ensures the ability of our food producers to withstand and adapt to climate change, thereby ensuring the security of our food supply (SDG 13). AIn has multiple consequences that have a cascading impact, including the alleviation of hunger (SDG 2) and affecting the economic development of the country. Thus, AIn has played a crucial role in providing support to the agriculture industry in managing the impacts of climate change while also serving as a means of reducing risk over the years. But certain literature highlights that AIn is considered a risk-mitigating strategy but has a limited ability to effectively control the hazards inherent in the sector [7]. The challenges highlighted are that the appropriateness of AIn relies on assessing its cost and the specifications of risk covered [8]. Further, it is seen as a supplementary method of risk reduction strategy for farmers compared to other agricultural approaches [9]. So, it would be worth examining whether the strategy of AIn has a high impact on managing the risk in the agriculture sector.

The historical development of AIn began with the Uruguay Round Agreement on Agriculture in 1986, which integrated agriculture into multilateral rules, leading to the Green Box Agreement in 1991 [10]. Thus, by 2007 more than 100 countries supported AIn through their programs and schemes [11]. In 2022, the AIn market globally was valued at \$38.5 billion (bn) [12]. In the Indian context, AIn began in 1915 in Mysore with the proposal of a rain insurance system for farmers to protect them against drought. This system used area-based approach. Following independence, discourse on AIn intensified, focusing on the merits of individual vs area-based insurance. The initial major endeavour was the Pilot Crop Insurance Scheme (PCIS) in 1979, which was subsequently terminated in 1999. The National Agricultural Insurance Scheme (NAIS) was established in 1999 to enhance coverage and alleviate risks associated with natural disasters. The Modified National Agricultural Insurance Scheme (MNAIS) was implemented in 2010, enhancing the existing framework. The Weather Based Crop Insurance Scheme (WBCIS) was initiated in 2007, succeeded by the Coconut Palm Insurance Scheme (CPIS) [13]. Consequently, as per the economic survey of India (2023–24), India has predominantly been an agrarian economy, with the sector contributing 18.2% to the country's GDP; the significance of AIn cannot be overlooked [14].

In India, Pradhan Mantri Fasal Bima Yojana (PMFBY) is the current primary program for AIn which has been implemented for the past eight years. Currently, the PMFBY 2.0 scheme (2021–2025) incorporates sufficient modifications to enhance its efficiency and efficacy compared to its predecessor. This scheme consolidated various previous insurance schemes into a single, comprehensive program aimed at reducing the premium burden on farmers and ensuring early claim settlements [15]. It operates under a public-private partnership model, involving the central and state governments, insurance companies, and banks, and offers the lowest premium rates in India's history of crop insurance—2% for Kharif crops, 1.5% for Rabi crops, and 5% for commercial and horticultural crops. It implements an individual-based insurance approach, which is different from the area-based approach of its predecessor. Further, for the scheme the central government's premium subsidy for northeastern states is 90%, allocating 0.5% for ICE efforts, and granting states autonomy in crop combinations. It also introduces technology solutions like smart sampling techniques for crop cutting experiments [16].

The primary objective is to analyse the extent and effectiveness of the PMFBY in terms of its impact on the farmers through the lenses of three variables awareness, transparency, and satisfaction.

2. Literature Review

The AIn and PMFBY were introduced to stabilize farmers' incomes, encourage the adoption of modern agricultural practices, and ensure the flow of credit to the agriculture sector. The scheme in India has sparked widespread interest among policymakers and researchers. There is a wealth of literature available related to AIn and PMFBY in India, which highlights its significance and limitations, examines its implementation, challenges, and impact on the farmers' livelihoods. However, a comprehensive assessment of impact through different parameters is lacking.

As per the available data from the PMFBY dashboard there has been a significant increase in the area under AIn, reflecting its acceptance among farmers in India. Income-related assessments on AIn show that a moderate positive impact on income generation for farmers in India [17]. Awareness is the primary factor that influences decision-making among farmers, leading to satisfaction with the related scheme [18, 19].

When it comes to timely claim settlements, the efficiency of the process plays a vital role in assisting farmers affected by crop losses [20]. Thus, timely claim settlement is critical for recovery and reinvestment for the coming season for farmers. There have been delays in claim settlements regarding crop losses, which are persistent in certain regions of India. This leads to a decrease in trust and enrollment among farming communities [21]. Technological advancements in the scheme have the potential to enhance the transparency, but although integration of technology has been done in the scheme, its application is still uneven across regions. This is due to many factors, such as the availability of technological infrastructure, literacy, and economic factors [22]. Furthermore the crop yield data, which is essential for claim settlements, has been found to be inaccurate, and the use of outdated technology is far from the ground reality [23]. The public disclosure of claim settlements and premium payments on government portals has not been properly executed, resulting in many farmers being uninformed about the status of their claims [21]. The awareness factor related to the important guidelines is also low among marginalized and semi-medium farmers, which is reflected in the participation data and claim settlements. Additionally, many farmers in remote locations lack sufficient knowledge of the availing process and benefits of the scheme, which undermines the satisfaction factor [24]. Thus, limited awareness, accompanied by inconsistent assessment of crop loss creates a perception of inequality which is a factor for the lack of trust and confidence among farmers in India [23].

To address the crop yield data, the use of modern technologies such as drones, AI, and remote sensing is suggested [25]. Furthermore, inclusive participation of local governance and local farmer organizations can enhance the inclusivity and effectiveness of the AIn schemes in India [26]. Thus, there are wicked problems for the effective management of such a large-scale AIn program across various states and agri-climatic zones. As the scheme was introduced to stabilize farmers' incomes, encourage the adoption of modern agricultural practices, and ensure the flow of credit to the agriculture sector, numerous literature studies reveal that no comprehensive strategy has been adopted to assess the perceived impact (PI) of agriculture insurance and PMFBY. Most of the literature on AIn and PMFBY in India lacks a comprehensive assessment of PI based on factors like awareness, satisfaction, and transparency, focusing mainly on crop yield, farmers' income, and financial settlements.

This study examines the PI of the scheme by using factors of policy outcomes like awareness, transparency, and satisfaction, which have a direct influence on the effectiveness of PMFBY. The notion of transparency, which pertains to the clarity and availability of information on policies and their execution, has been thoroughly examined in the literature on public administration. Transparent processes are thought to improve the accountability of public agencies and promote confidence among stakeholders, which can consequently have a beneficial influence on the perceived effectiveness of governmental initiatives [27, 28]. Awareness, a vital factor, relates to the degree to which recipients are knowledgeable about the specifics, advantages, and processes of a policy or program. Greater levels of awareness are typically linked to heightened engagement and more efficient utilisation of the advantages offered by governmental programs. Research has demonstrated that awareness campaigns have a substantial impact on increasing participation and effective execution of social protection programs [29].

Satisfaction, the third independent variable in the model, is frequently included as an indicator of perceived achievement from the beneficiaries' standpoint. This highlights the importance of meeting the expectations of beneficiaries in order to achieve long-term success and maintain the perceived legitimacy of policy initiatives. Prior studies on public service delivery suggest that satisfaction is strongly correlated with both the level of service delivery and the transparency of the processes involved, thereby affecting the overall effectiveness of the program [30, 31].

Hypotheses: There is a positive relationship between perceived impact and the policy outcome factors awareness, transparency and satisfaction.

3. Research Design and Methodology

3.1. Research Design

The research design for this study follows a sequential exploratory approach of mixed-methods in which it incorporates both qualitative and quantitative techniques. It is structured into two phases: a qualitative phase and a quantitative phase. In the qualitative phase in-depth interviews are used as a tool for data collection. In this phase, key stakeholders, including government officials, insurance company representatives, research experts, and farmers were interviewed. This phase aims to identify issues and opportunities for the PMFBY and forms the foundation for the subsequent quantitative phase. In the quantitative phase, we test our hypotheses through a large-scale survey of farmers, using cluster sampling to ensure comprehensive coverage of the country's geography. This design allows for a robust analysis of the scheme's impact and the identification of areas for improvement [32].

3.2. Data Collection Strategies

Data collection was carried out in two distinct phases. The first phase involved qualitative data collection through 15 in-depth interviews with key stakeholders using semi-structured questionnaires to capture a wide range of perspectives. In this stage, a purposive sampling technique was employed to ensure the inclusion of diverse voices and perspectives. The interviews were conducted across four selected states: Kerala, Madhya Pradesh, Rajasthan and Uttar Pradesh. The outcome of this stage was the identification of key areas and factors for the development of a structured questionnaire for the next phase. In this phase, data collection was done through a structured questionnaire, and we targeted a total of 3,000 farmers across the four selected states. The cluster sampling method was utilized to select respondents from varied geographical regions, agricultural patterns, and climate conditions, ensuring a representative sample.

The total population of farmers benefiting from the PMFBY scheme dashboard (2022 Karif) was 1,85,95,722 farmers who were enrolled and for whom premiums were paid. The clustering of selected states was done based on geographical location (West, South, and Central) and their enrolment of farmers. Further, in the second cluster, districts in each state were selected based on their geographical location. The survey tool was made in both language Hindi and English and administered via Google Forms. Despite concerns about data inconsistency with Google Forms [33], these were mitigated through clear guidelines and robust validation methods [34].

A pilot study was conducted in Kerala in December 2024, leading to the identification of potential challenges, which were addressed through targeted interventions, including training workshops for field investigators, ensuring robust internet access, and having an author accompany the research team during data collection. The process was further refined through daily meetings to review and address any emerging issues.

The data was collected from November 2023 to January 2024, with a total of 3,008 responses from four states (**Figure 2**) to assess the impact and perceptions of PMFBY among farmers.

3.3. Age Distribution among Respondents for Selected States

The collection from the four states reveals that the age-wise distribution of respondents is diverse, with the majority falling within the middle-age categories. The largest age group is aged 45–53, followed by 36–

44 and 54–62. Younger respondents make up 15.63%, while older age groups have lower representation. This reflects a predominantly middle-aged population, potentially influencing perspectives on agricultural practices and insurance schemes like PMFBY. The presence of older respondents provides insights into long-term farmers' experiences. (**Figure 3**).

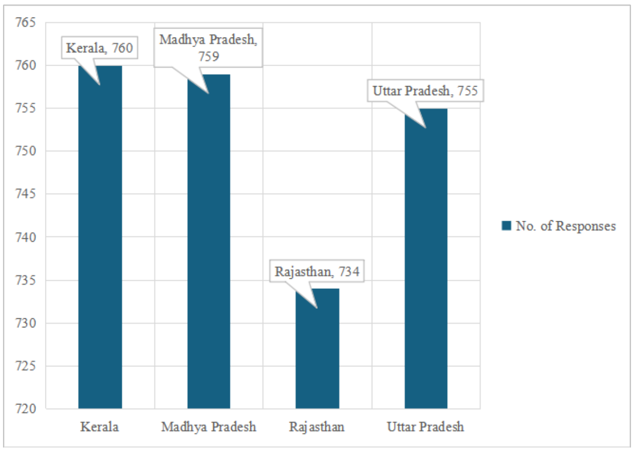

Figure 2. Distribution of respondents among the selected states.

Source: Compiled by author in Tableau.

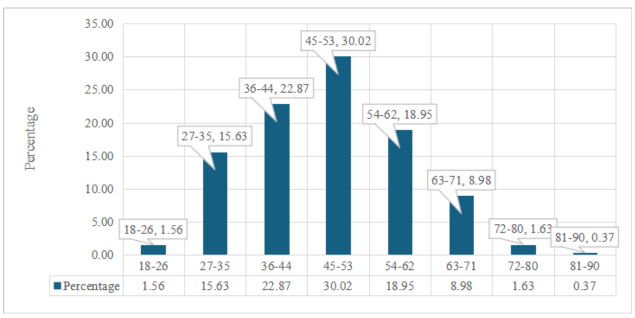

Figure 3. Age-wise distribution of respondents among the selected states.

Source: Compiled by author using Tableau.

Additionally, the income distribution data reveals that there are significant regional variations in economic status among respondents. In Kerala, 97.63% of respondents reported an annual income of less than INR 1 lakh, indicating a concentration of lower-income farmers. In Madhya Pradesh, 50.86% of respondents reported incomes between INR 1 lakh and 5 lakh, while 30.04% fell into higher income brackets. Rajasthan's distribution was similar, with 47.28% earning less than INR 1 lakh and 43.73% falling into the INR 1 lakh to 5 lakh category. Uttar Pradesh's 58.94% reported incomes of less than INR 1 lakh, indicating a predominance of lower-income farmers (**Figure 4**). Similarly, the educational levels of respondents in Kerala, Madhya Pradesh, Rajasthan, and Uttar Pradesh are varied, indicating a significant level of illiteracy among the farming community. In Kerala, 53.16% of respondents have no formal education, while 25.92% have completed secondary education. Madhya Pradesh has a more balanced distribution, with 26.09% having completed primary education and 19.76% being graduates. Rajasthan has a similar distribution, with 25.20% having completed primary education and 17.85% having completed higher secondary education. Uttar Pradesh has a diverse educational profile, with 19.74% having no formal education and 19.07% being graduates (**Figure 5**). The diversity in social backgrounds was seen in the caste data from the states, which can impact access to resources and benefits from government schemes like the Pradhan Mantri Fasal Bima Yojana (PMFBY). Uttar Pradesh has the highest representation of Other Backward Classes (OBC), followed by Kerala (12.73%), Madhya Pradesh (10.11%), and Rajasthan (10.27%). The General caste category has lower representation, suggesting a smaller farming population. The Scheduled Caste category has moderate representation, with Uttar Pradesh having the highest representation. The Scheduled Tribe category is more prominent in Rajasthan (**Figure 6**).

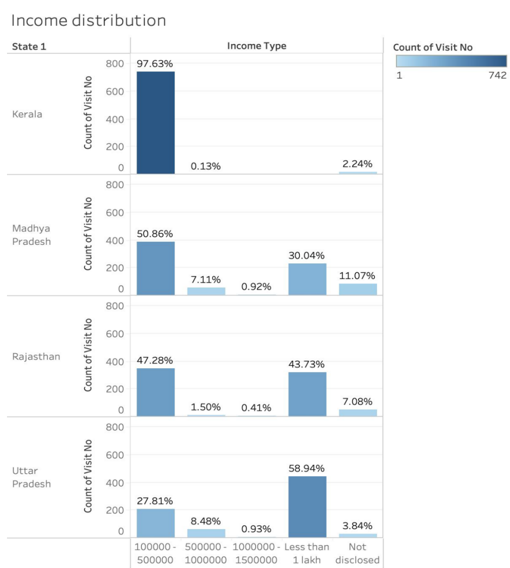

Figure 4. Income-wise distribution of respondents among the selected states.

Source: Compiled by author using Tableau.

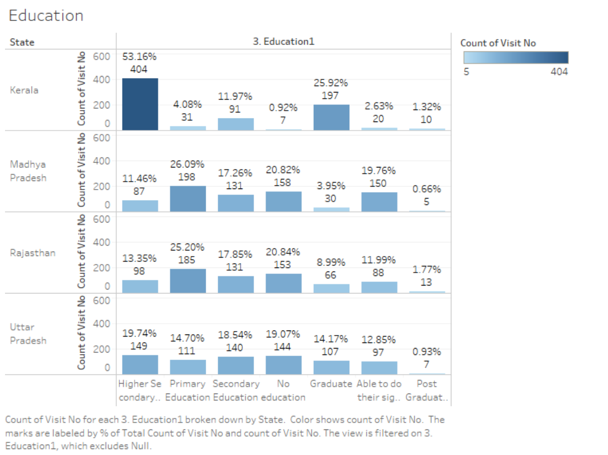

Figure 5. Education-wise distribution of respondents among the selected states.

Source: Compiled by author using Tableau.

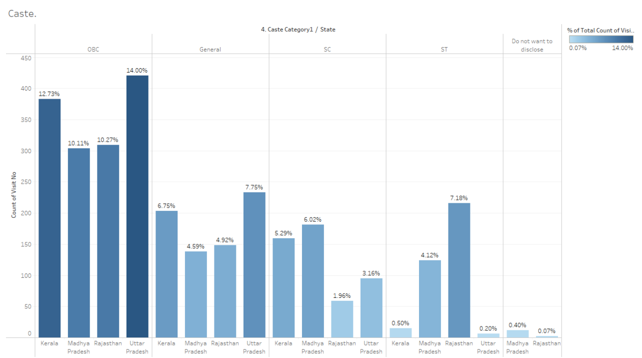

Figure 6. Caste-wise distribution of respondents among selected states.

Source: Compiled by author using Tableau.

This diversity observed among the groups of data underscores the effectiveness and robustness of the data collection strategies employed, indicating that the data collected is well-suited to provide comprehensive insights into the varied experiences and needs of the farming community. The diversity is essential for understanding the socio-economic dynamics at play and the potential differential impacts of schemes like PMFBY across different states and social groups.

3.4. Model and Estimators

A multiple linear regression model was used to examine the associations between the independent variables (Transparency, Awareness, and Satisfaction) and the dependent variable (Impact) [35]. The Pearson correlation coefficients demonstrated robust, positive associations among all the variables, hence validating the utilisation of regression analysis to quantify these associations. Based on the statistically significant correlations, the regression model will enable us to estimate the influence of each independent variable while accounting for the impacts of the other variables. The significance of the predictors will be evaluated using p-values, and the magnitude of their influence will be quantified by standardised regression coefficients (Beta coefficients).

The specification of the model is as follows:

$$Impact_i = \beta 0 + \beta 1 Transparency_i + \beta 2 Awareness_i + \beta 3 Satisfaction_i + \epsilon_i$$

Where:

- $Impact_i$ represents the perceived impact of the PMFBY scheme for observation *i*.
- $Transparency_i$, $Awareness_i$, and $Satisfaction_i$ are the independent variables corresponding to the transparency, awareness, and satisfaction levels reported by the respondents for observation *i*.
- β0 is the intercept of the model.
- β1, β2, and β3 are the coefficients that measure the impact of each independent variable on the dependent variable.
- ϵi is the error term, capturing the unobserved factors that might affect the perceived impact.

Thus, the paper's utilisation of multiple linear regression aligns with the current body of research that investigates the connections between policy variables and their resultant effects. For example, Grimmelikhuijsen (2012) showed how regression analysis may be used to estimate the influence of transparency on public trust[18], while Banerjee et al. (2015) used similar techniques to evaluate the effect of awareness on the success of social programs[36]. The average satisfaction level index is developed using regression analysis, which highlights the potency of the weather-based insurance scheme in Maharashtra. This model is a win-win situation for all the stakeholders[37]. The selected model facilitates a concurrent analysis of the effects of transparency, awareness, and satisfaction on the perceived impact of PMFBY, leading to a thorough comprehension of the scheme's efficacy.

4. Discussion—Results and Analysis

First the descriptive statistics analysis for the dependent and independent variables. Descriptive statistics are frequently employed in impact studies to succinctly summarise important variables, offering a precise comprehension of major tendencies and variabilities. Examples include Bhuiyan et al., who utilize mean, standard deviation measures and descriptive statistics to check the effect of agricultural insurance in Guangdong Province on farmers' income [38], and Patel, Singh and Chaturvedi highlighting response distribution in health schemes [39]. The descriptive statistics analysis in the regression model is summarized in **Table 1**. The mean scores for Impact, Awareness, Satisfaction, and Transparency were 3.2444, 3.1602, 3.1894, and 3.1847, respectively. The standard deviations for these variables ranged between 0.71453 and 0.80170. The results indicate that the respondents, on average, gave moderate scores for all the categories tested, suggesting a consistent central tendency within the dataset. The standard deviations of the responses showed a consistent level of variability across the variables, indicating a similar amount of spread around the mean for each factor [40].

Table 1. Descriptive statistic analysis of perceived impact, awareness, satisfaction, and transparency for PMFBY scheme.

Descriptive Statistics			
	Mean	**Std. Deviation**	**N**
Impact	3.2444	0.79284	3008
Awareness	3.1602	0.71453	3008
Satisfaction	3.1894	0.76568	3008
Transparency	3.1847	0.80170	3008

Source: Authors' analysis in SPSS.

Further the paper uses the approach to examining correlations between the independent and dependent variables which is in consistent with prior studies that have analysed the impact of government schemes. For instance, Sharma et al. (2018) found similar strong correlations between variables such as service quality, transparency, and satisfaction in their study of public health interventions, emphasizing the importance of these factors in determining the success of government programs. The correlation analysis reveals significant positive relationships between the dependent variable (Impact) and the independent variables—Awareness, Satisfaction, and Transparency. Specifically, the Pearson correlation coefficients indicate that Awareness ($r = 0.782$, $p < 0.001$), Satisfaction ($r = 0.870$, $p < 0.001$), and Transparency ($r = 0.829$, $p < 0.001$) are all strongly correlated with the perceived impact of the PMFBY scheme. These findings suggest that as awareness, satisfaction, and transparency increase, so does the perceived impact of the scheme. Furthermore, the strong correlations observed between the independent variables themselves, particularly between Satisfaction and Transparency ($r = 0.908$, $p < 0.001$), highlight the interconnectedness of these factors. While this suggests potential multicollinearity, further regression analysis will assess the robustness of the model (**Table 2**).

Robustness & Model Significance

The regression model shows a strong fit to the data, explaining 76.8% of the variance in the dependent variable (Impact) by the combined effect of awareness, satisfaction, and transparency. The model's reliability is confirmed by a significant F-change, and its adequacy and parsimonious nature are supported by selection criteria. Transparency, awareness, and satisfaction are significant predictors of the perceived impact of the PMFBY scheme, suggesting that enhancing these factors can enhance the scheme's effectiveness (**Table 3**).

The collinearity diagnosis assesses the multicollinearity among the independent and dependent variables. The multicollinearity analysis helps in checking the robustness of the regression analysis and coefficient analysis. The examination of the model for the de-

Table 2. Correlation analysis of perceived impact, awareness, satisfaction and transparency for PMFBY scheme.

Correlations Analysis					
		Impact	**Awareness**	**Satisfaction**	**Transparency**
Pearson correlation	Impact	1.000	0.782	0.870	0.829
	Awareness	0.782	1.000	0.861	0.811
	Satisfaction	0.870	0.861	1.000	0.908
	Transparency	0.829	0.811	0.908	1.000
Sig. (1-tailed)	Impact	.	<0.001	<0.001	<0.001
	Awareness	0.000	.	0.000	0.000
	Satisfaction	0.000	0.000	.	0.000
	Transparency	0.000	0.000	0.000	.
N	Impact	3008	3008	3008	3008
	Awareness	3008	3008	3008	3008
	Satisfaction	3008	3008	3008	3008
	Transparency	3008	3008	3008	3008

Source: Authors' analysis in SPSS.

Table 3. Model summary of perceived impact, awareness, satisfaction and transparency for PMFBY scheme.

Model Summary[ab]													
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Selection Criteria			
					R Square Change	F Change	df1	df2	Sig. F Change	Akaike Awareness Criterion	Amemiya Prediction Criterion	Mallows' Prediction Criterion	Schwarz Bayesian Criterion
1	0.876[a]	0.768	0.768	0.38194	0.768	33170.782	3	3004	<0.001	−5786.369	0.232	4.000	−5762.333

a. Predictors: (Constant), transparency, awareness, satisfaction
b. Dependent variable: Impact
Source: Authors' analysis in SPSS.

pendent variable (perceived impact) and independent variables (Awareness, Satisfaction and Transparency) shows that they contribute uniquely to predicting the dependent variable (Impact), without substantial overlap in their explanatory power (**Table 4**).

The residual statistics provide insights into the model's fit and the distribution of errors. The residual statistics of the paper suggest that the model provides a good fit to the data, with predictions closely aligning with actual values, and no significant outliers or influential points that could distort the model's findings. This reinforces the reliability of the regression results and the robustness of the conclusions drawn from the analysis [40] (**Table 5**).

Table 4. Collinearity diagnosis of perceived impact, awareness, satisfaction and transparency for PMFBY scheme.

Collinearity Diagnostics[a]							
Model	Dimension	Eigenvalue	Condition Index	Variance Proportions			
				(Constant)	Awareness	Satisfaction	Transparency
1	1	3.947	1.000	0.00	0.00	0.00	0.00
	2	0.038	10.204	0.92	0.01	0.02	0.04
	3	0.010	19.766	0.07	0.79	0.01	0.34
	4	0.005	29.100	0.00	0.20	0.97	0.63

a. Dependent variable: Impact
Collinearity diagnostics: The diagnostics do not indicate significant multicollinearity issues, suggesting that the predictors are not overly correlated with one another. This means each independent variable contributes uniquely to predicting the dependent variable.

5. Limitation of the Study

The study explores the relationship between transparency, awareness, satisfaction, and the impact of the Pradhan Mantri Fasal Bima Yojana (PMFBY). However, it has limitations such as a cross-sectional design [41], reliance on self-reported data [42], and generalizability due to the geographic and socio-economic context [43]. The study also lacks control for external factors influencing the perceived impact of the PMFBY, such as policy

Table 5. Residuals statistics of perceived impact, awareness, satisfaction, and transparency for PMFBY scheme.

Residuals Statistics[a]					
	Minimum	**Maximum**	**Mean**	**Std. Deviation**	**N**
Predicted value	1.2148	4.9291	3.2444	0.69488	3008
Std. Predicted value	−2.921	2.424	0.000	1.000	3008
Standard error of predicted value	0.007	0.050	0.013	0.005	3008
Adjusted predicted value	1.2155	4.9326	3.2444	0.69485	3008
Residual	−2.61732	1.94373	0.00000	0.38175	3008
Std. Residual	−6.853	5.089	0.000	1.000	3008
Stud. Residual	−6.868	5.091	0.000	1.000	3008
Deleted residual	−2.62938	1.94495	−0.00003	0.38239	3008
Stud. Deleted residual	−6.922	5.112	0.000	1.001	3008
Mahal. Distance	0.008	50.327	2.999	3.361	3008
Cook's distance	0.000	0.054	0.000	0.002	3008
Centered leverage value	0.000	0.017	0.001	0.001	3008

a. Dependent variable: Impact
Source: Authors' analysis in SPSS.

changes, economic conditions, or climatic events [44]. Future research should incorporate longitudinal data and control for these external variables to provide a more comprehensive analysis.

6. Conclusions

Thus, the study analyses the impact of PMFBY on farmers in four Indian states. It finds that transparency, awareness, and satisfaction significantly influence the scheme's effectiveness. Satisfaction is the most influential factor, followed by transparency and awareness. The study suggests an integrated approach to policy implementation. However, limitations include a cross-sectional design and self-reported data, requiring future research using longitudinal designs and advanced statistical techniques. In conclusion, the study highlights the importance of addressing the interconnected factors of transparency, awareness, and satisfaction to maximize the impact of the PMFBY. Policymakers should focus on enhancing these areas to ensure that the benefits of the scheme are fully realized by the farming community. This will not only improve the effectiveness of the PMFBY but also contribute to the broader goal of enhancing agricultural resilience in India. Further research using these interconnected factors of transparency, awareness and satisfaction should be done to analyse such policies in the future.

Author Contributions

S.D.—concept development and data collection; G.D.R.—paper development; S.A.—data cleaning and analysis.

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Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

Data Availability Statement

The datasets generated during and/or analyzed during the current study are available from the corresponding author upon reasonable request.

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Conflicts of Interest

The authors declare that they have no conflict of interest.

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