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A study on Key determinants influencing the adoption and effectiveness of crop insurance schemes for Achieving Sustainable Agricultural Growth

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Abstract
This study investigates the key determinants influencing the adoption and effectiveness of crop insurance schemes to achieve sustainable agricultural growth in Haryana, India. Given the critical role of crop insurance in mitigating agricultural risks and enhancing farmers' resilience against climatic and market uncertainties, understanding the factors that drive its adoption and perceived effectiveness is vital for policy formulation and program implementation. Utilizing data collected from 400 farmers across Haryana, the study employs Structural Equation Modeling (SEM) through Smart PLS 4 to analyze complex relationships among constructs including awareness, accessibility, trust in the insurance scheme, perceived effectiveness, and sustainable agricultural growth. The findings reveal that awareness and accessibility significantly influence farmers' trust in crop insurance schemes, which in turn positively affects their perception of the scheme's effectiveness. Furthermore, perceived effectiveness is identified as a crucial driver of sustainable agricultural growth, mediating the effects of awareness, accessibility, and trust. These results underscore the importance of comprehensive awareness campaigns and improved accessibility mechanisms to foster trust, which is pivotal in enhancing the perceived value and adoption of crop insurance. The mediation analysis highlights the interconnectedness of these factors, suggesting that isolated interventions are insufficient without simultaneously addressing trust and perceived benefits. This study contributes to the extant literature by providing empirical evidence from a region-specific context, enhancing understanding of the behavioral and institutional dimensions of crop insurance adoption. The research offers practical implications for policymakers, recommending integrated strategies that combine education, infrastructure improvements, and transparent communication to bolster insurance uptake and effectiveness. Limitations include the use of cross-sectional data and focus on a single geographic region, with suggestions for future research involving longitudinal designs and broader socio-economic variables. Overall, the study provides a nuanced framework for improving crop insurance schemes as a mechanism for sustainable agricultural development, offering valuable insights for stakeholders aiming to enhance food security and farmer livelihoods in Haryana and similar agrarian contexts globally.

Keywords: *Crop insurance, Adoption determinants, Sustainable agricultural growth, Trust, Awareness, Structural Equation Modeling (SEM).*

1.INTRODUCTION

Agriculture remains the backbone of many developing economies, not only as a provider of food security and rural employment but also as a cornerstone for sustainable economic development (FAO, 2021; World Bank, 2020). However, the sector is intrinsically vulnerable to a multitude of risks, including climatic extremes, market volatility, pest outbreaks, and unpredictable rainfall patterns, which severely threaten agricultural productivity and farmer livelihoods (Hazell et al., 2010; IPCC, 2021). In this context, crop insurance emerges as a vital risk mitigation mechanism, enabling farmers to hedge against potential crop failures and income losses, thus fostering long-term agricultural resilience and sustainability (Mahul & Stutley, 2010; Miranda & Farrin, 2012). Crop insurance, when effectively implemented, serves as both

a financial safeguard and a developmental tool that aligns with the broader goals of sustainable agriculture as outlined in the United Nations Sustainable Development Goals (SDG 1, 2, and 13) (UNDP, 2019; FAO, 2020). Despite its theoretical potential, the actual adoption and effectiveness of crop insurance schemes remain inconsistent and regionally varied, especially in countries like India where agriculture is primarily smallholder-based and climate-vulnerable (Rao et al., 2016; Ceballos et al., 2019). In India, the government has implemented multiple insurance schemes over the years, including the National Agricultural Insurance Scheme (NAIS), Modified NAIS (MNAIS), and the flagship Pradhan Mantri Fasal Bima Yojana (PMFBY), aimed at increasing farmer participation and minimizing financial distress (Choudhury et al., 2016; Dev & Rao, 2015). However, empirical evidence suggests that uptake remains low due to factors such as lack of awareness, delayed claim settlements, high premium costs, inadequate institutional outreach, and distrust in government mechanisms (Clarke et al., 2012; Meena et al., 2019; Narayanan et al., 2020). Moreover, there exists a crucial gap between policy design and field-level implementation, often influenced by region-specific socioeconomic, psychological, and institutional factors (Giné & Yang, 2009; Cole et al., 2013). Understanding the key determinants that influence both the adoption and operational effectiveness of crop insurance schemes is thus imperative for policy formulation and improvement of implementation strategies (Binswanger-Mkhize, 2012; Jensen & Barrett, 2017). Adoption is influenced by a range of demographic variables such as age, education level, landholding size, and farming experience, while institutional determinants include access to credit, extension services, trust in agencies, and communication efficacy (Dercon et al., 2014; Hill & Viceisza, 2012). Psychological and behavioral factors—like risk perception, previous loss experience, and attitude toward innovation—also play a crucial role in shaping farmers' willingness to adopt insurance products (Sherrick et al., 2004; McIntosh et al., 2013). Effectiveness, on the other hand, is measured not only by the number of farmers enrolled but also by the timeliness of claim disbursals, adequacy of coverage, transparency in processes, and farmers' overall satisfaction with the scheme (Chantarat et al., 2013; Carter et al., 2014). Several scholars argue that crop insurance effectiveness is further enhanced when integrated with other risk management tools such as weather forecasts, early warning systems, and precision agriculture technologies (Hazell & Hess, 2010; Norton et al., 2015). From the sustainability perspective, crop insurance contributes to reducing vulnerability, enhancing adaptive capacity, and promoting financial inclusion in rural areas—thereby making agriculture more robust against shocks and ensuring continuity of production cycles (Surminski & Oramas-Dorta, 2014; Hellmuth et al., 2009). The state of Haryana, being an agrarian economy and a key contributor to India's food grain production, provides a unique context to investigate the interplay of these determinants. Although Haryana has relatively better access to irrigation, technology, and market infrastructure, challenges in crop loss assessments, premium affordability, and limited awareness among small and marginal farmers persist (GoH, 2022; NABARD, 2021). Studies specific to Haryana have indicated that a significant proportion of farmers either do not enroll or drop out of insurance schemes due to procedural complexities, perceived inadequacy of benefits, and lack of trust in claim mechanisms (Kaur & Sidhu, 2020; Singh & Bhogal, 2018). Furthermore, despite efforts by state and central governments to streamline the insurance ecosystem through digital platforms and satellite-based crop monitoring, ground-level bottlenecks related to implementation and farmer inclusion continue to hamper effectiveness (MoA&FW, 2020; IFPRI, 2021). Thus, this study becomes vital in bridging the empirical and theoretical gaps by holistically analyzing the factors that determine not only the adoption but also the real-world performance of crop insurance schemes in contributing toward sustainable agricultural growth. The integration of socio-economic variables with behavioral, institutional, and policy dimensions provides a multi-layered understanding of how these determinants interact and affect scheme outcomes (Mishra et al., 2022; Ghosh & Mishra, 2020). This study also responds to scholarly calls for contextualized, region-specific analyses that inform targeted interventions and inclusive insurance designs (Mahul et al., 2012; World Bank, 2021). Importantly, it aligns with recent policy dialogues on transforming agricultural risk management from reactive compensation toward proactive resilience building (OECD, 2020; GIZ, 2022). By identifying and categorizing the critical drivers and barriers to effective crop insurance in Haryana, the research seeks to provide actionable recommendations for stakeholders—including policymakers, financial institutions, insurance providers, and farmer collectives—who are directly or indirectly involved in shaping agricultural

sustainability. In light of climate change and frequent extreme weather events, enhancing the resilience of the farming community through efficient risk management systems like crop insurance is no longer an option but a necessity (IPCC, 2021; FAO, 2022). It further aims to provide empirically grounded insights that support policy innovation and adaptive strategies for ensuring long-term food and income security in agrarian states like Haryana.

1.1 Research Objectives

1) *To investigate the impact of socio-economic factors, institutional support, and awareness/trust on the adoption of crop insurance schemes among farmers in Haryana.*
2) *To examine how the adoption of crop insurance schemes influences their perceived effectiveness in mitigating agricultural risks and supporting farmer welfare.*
3) *To analyze the direct and mediating effects of crop insurance adoption and effectiveness on achieving sustainable agricultural growth.*

1.2 Research Questions

How do socio-economic characteristics, institutional support mechanisms, and farmer awareness/trust influence the adoption of crop insurance schemes?

What is the relationship between the adoption of crop insurance schemes and their perceived effectiveness in ensuring risk protection and timely benefits?

To what extent do the adoption and effectiveness of crop insurance schemes contribute—independently or jointly—to sustainable agricultural growth?

2.Literature Review

The literature review for this paper includes a comprehensive exploration of scholarly perspectives, theoretical underpinnings, and empirical findings related to the adoption and effectiveness of crop insurance schemes, with a focus on their contribution to sustainable agricultural growth. Structured around three major themes, the review first examines socio-economic, institutional, and behavioral determinants influencing farmers' decision to adopt crop insurance—drawing on factors such as income, education, risk perception, policy trust, and access to credit. The second theme evaluates the operational effectiveness of crop insurance, emphasizing issues like claim settlement, moral hazard, basis risk, and the role of technology in enhancing transparency and efficiency. The third theme situates crop insurance within the broader context of sustainable agricultural development, discussing how well-designed insurance can promote climate resilience, rural stability, and long-term investment in agriculture. Across these themes, the review incorporates high-quality citations from globally recognized scholars, reports, and policy evaluations, offering both international and Indian perspectives. It also identifies gaps in current research, such as lack of farmer-centric design and low insurance literacy, thereby justifying the need for this study. Overall, the literature review provides a strong conceptual and empirical foundation for the research framework, objectives, and SEM-based model development.

2.1: Socio-Economic, Institutional, and Behavioral Determinants of Crop Insurance Adoption.

The adoption of crop insurance schemes is significantly influenced by a combination of socio-economic, institutional, and behavioral factors that shape farmer attitudes, decision-making, and risk perceptions. Socio-economic attributes such as age, education, income, landholding size, and farming experience have been frequently cited as key variables influencing insurance uptake (Giné et al., 2008; Mahul & Stutley, 2010; Cai et al., 2015). Farmers with higher education levels and greater access to credit and extension services are more likely to comprehend and engage with complex financial products such as crop insurance (Dercon et al., 2014; Cole et al., 2013). Likewise, larger landholders often show a higher willingness to pay for insurance premiums due to the scale of risk exposure (Clarke & Dercon, 2016; Hill et al., 2019). Institutional factors such as the presence of local insurance agents, government subsidies, and access to formal information channels also play a critical role in shaping adoption behavior

(Binswanger-Mkhize, 2012; Ramaswami et al., 2018). Moreover, behavioral determinants like risk aversion, previous experience with insurance products, and trust in government institutions have a profound influence on farmers' decision-making (Mobarak & Rosenzweig, 2013; Karlan et al., 2014). In the Indian context, where informal risk-sharing mechanisms and traditional coping strategies are still prevalent, behavioral inertia and lack of awareness often undermine the success of crop insurance programs (Narayanan et al., 2019; Bhende, 2005). Institutional failures—such as delays in claim settlements and lack of transparency—further erode farmer trust and impede scheme adoption (Carter et al., 2014; Vandeveer et al., 2000). The role of policy incentives and targeted education campaigns is therefore crucial in facilitating the behavioral transition toward formal insurance products (Chantarat et al., 2013; Takahashi et al., 2016). In sum, the adoption of crop insurance schemes in agrarian economies like India hinges on an intricate interplay of structural inequalities, policy implementation, and socio-psychological readiness.

2.2: Effectiveness of Crop Insurance Schemes in Enhancing Risk Mitigation and Agricultural Stability.

The effectiveness of crop insurance schemes in achieving their intended risk mitigation goals is contingent upon not just adoption levels, but also operational efficiency, stakeholder coordination, and the alignment of scheme design with ground realities. Effective crop insurance provides timely compensation, protects against yield or revenue loss, and reduces farmers' dependence on informal coping strategies (Hazell et al., 1986; Barnett & Mahul, 2007). However, empirical evidence from developing countries has shown a mixed record of performance, with challenges related to moral hazard, basis risk, and delays in claim disbursement (Miranda & Farrin, 2012; Clarke et al., 2012). In India, the Pradhan Mantri Fasal Bima Yojana (PMFBY), while ambitious in scope, has faced criticism over delayed payments, low claim ratios, and weak grievance redressal mechanisms (Kumar et al., 2017; Narayanan et al., 2019). Studies indicate that the perceived effectiveness of insurance schemes significantly influences repeat participation and farmer satisfaction (Greatrex et al., 2015; Ward et al., 2018). Moreover, institutional capacity—including insurer accountability, regulatory oversight, and use of technology for damage assessment—has a profound effect on scheme reliability (Carter et al., 2017; Jensen & Barrett, 2017). Technological interventions such as remote sensing, satellite imagery, and mobile-based claim processing have shown potential in reducing administrative inefficiencies and enhancing trust in the system (Hellmuth et al., 2009; Jain et al., 2015). From a risk management perspective, insurance is more effective when embedded in a larger financial ecosystem including access to credit, extension services, and climate-resilient farming practices (Skees et al., 2008; Mahul & Stutley, 2010). Farmers' feedback and participation in policy formulation can further improve contextual relevance and effectiveness (Tadesse et al., 2015; Bhattamishra & Barrett, 2008). Overall, while crop insurance remains a promising tool for agricultural risk mitigation, its success depends on systemic reforms, operational efficiency, and participatory implementation models that address both financial and non-financial constraints.

2.3 Crop Insurance and Its Contribution to Sustainable Agricultural Growth.

The broader developmental impact of crop insurance must be evaluated in the context of its contribution to sustainable agricultural growth, encompassing economic resilience, environmental stability, and social equity. Crop insurance, when effectively implemented, acts as a critical instrument for building farmer resilience against climatic shocks, price volatility, and natural disasters—factors that increasingly threaten food security and rural livelihoods (Hazell & Hess, 2010; Mechler et al., 2006). By protecting income and ensuring liquidity during crises, insurance schemes enable farmers to invest in productivity-enhancing inputs and adopt climate-smart technologies (Elabed & Carter, 2015; Hill & Robles, 2011). This in turn leads to improved farm incomes, reduced vulnerability, and enhanced agricultural productivity—key components of sustainable agricultural growth (De Janvry et al., 2011; Mahul & Stutley, 2010). Furthermore, crop insurance can reduce the reliance on distress migration and environmentally degrading practices like overuse of groundwater or expansion into marginal lands (Karlan et al., 2014; Clarke & Hill, 2013). In India, several studies have found a positive association between insurance coverage and investment in improved seeds, fertilizers, and machinery—an essential precursor to sustainable intensification (Ramaswami & Balasubramanian, 2019; Shankar et al., 2019). Moreover, inclusive insurance models that integrate gender perspectives and target marginal farmers promote social

equity and rural development (Chantarat et al., 2013; Takahashi et al., 2016). The integration of insurance with broader agri-policy frameworks such as climate adaptation plans, rural credit systems, and extension services strengthens its developmental impact (Carter et al., 2014; Giné & Yang, 2009). However, sustainable impact is hindered by systemic flaws like limited coverage, skewed enrollment toward wealthier farmers, and lack of transparency in claim settlement (Narayanan et al., 2019; Bhende, 2005). Thus, for crop insurance to serve as a lever for sustainable agricultural growth, it must be designed not just as a financial product, but as a strategic policy instrument aligned with rural development, environmental resilience, and equitable access.

3.RESEARCH METHODOLOGY

The research methodology adopted in this study is quantitative in nature and is designed to examine the key determinants influencing the adoption and effectiveness of crop insurance schemes for achieving sustainable agricultural growth in Haryana. The study utilized a structured questionnaire, which was developed by adapting and synthesizing validated scales and items from existing literature focused on crop insurance adoption and agricultural sustainability, specifically relevant to the regional context of Haryana. These scales were carefully reviewed and modified for local suitability, ensuring contextual relevance and content validity. The questionnaire was divided into several sections capturing demographic variables, socio-economic attributes, risk perception, awareness, accessibility, satisfaction, and sustainability outcomes. A purposive sampling technique was employed to select respondents, and data was collected from a total of 400 farmers across different districts of Haryana. These farmers were actively engaged in crop cultivation and had exposure to government or private crop insurance schemes. The data collection process involved field visits and direct interactions, ensuring reliable and accurate responses. Once collected, the data was coded, cleaned, and analyzed using Smart PLS 4, a robust statistical tool suited for Structural Equation Modeling (SEM). SEM was employed to test the hypothesized relationships between latent constructs and to validate the conceptual model developed from the literature. The software facilitated the assessment of reliability, validity, path coefficients, model fit indices, and mediation effects. This methodology enabled the researchers to evaluate the direct and indirect relationships among variables such as insurance awareness, accessibility, trust in schemes, and sustainability outcomes. The use of Smart PLS 4 was particularly suitable for the study due to its ability to handle complex models with multiple constructs and its non-parametric nature, which is appropriate given the non-normality often found in primary agricultural datasets. The methodological approach ensured both theoretical rigor and empirical robustness.

4.DATA ANALYSIS AND RESULTS

The Data Analysis and Results section of this study presents the statistical evaluation of the primary data collected from 400 farmers in Haryana to examine the key determinants influencing the adoption and effectiveness of crop insurance schemes for achieving sustainable agricultural growth. This section includes descriptive statistics to summarize demographic profiles, farming characteristics, and levels of awareness, satisfaction, and trust regarding crop insurance. It further involves construct reliability and validity testing through indicators such as Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) to ensure the internal consistency and convergent validity of the measurement model. Using Smart PLS 4, the study employs Structural Equation Modeling (SEM) to test hypothesized relationships between latent variables. The analysis includes path coefficient estimation, t-values, and p-values through bootstrapping to assess the significance of direct and indirect effects. Model fit indices such as SRMR and NFI are also reported to validate the model's overall adequacy. The results interpret the influence of variables like insurance awareness, accessibility, institutional support, and perceived benefits on adoption and effectiveness, ultimately linking them to sustainable agricultural outcomes. This section serves as the foundation for drawing meaningful conclusions and implications based on empirical evidence.

4.1 Demographic Factors

Table 4. 1: Demographic Profile of Respondents (N = 400)

Demographic Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	340	85.0%
	Female	60	15.0%
Age Group (Years)	Below 30	40	10.0%
	31–45	150	37.5%
	46–60	140	35.0%
	Above 60	70	17.5%
Education Level	Illiterate	40	10.0%
	Primary Education	100	25.0%
	Secondary Education	140	35.0%
	Graduate and Above	120	30.0%
Landholding Size	Less than 2 acres	110	27.5%
	2–5 acres	170	42.5%
	Above 5 acres	120	30.0%
Farming Experience	Less than 5 years	60	15.0%
	5–10 years	130	32.5%
	Above 10 years	210	52.5%
Enrollment in Crop Insurance	Yes	300	75.0%
	No	100	25.0%

Source: Author's Calculation in PowerBI.

The demographic profile of the 400 farmers surveyed in Haryana reveals significant insights into the sample composition relevant to the study on crop insurance adoption and effectiveness. The majority of respondents were male, comprising 340 farmers or 85% of the sample, while females accounted for 60 farmers or 15%. Age-wise, most farmers fell within the 31–45 years category, with 150 respondents (37.5%), followed closely by those aged 46–60 years, totaling 140 farmers (35%). Younger farmers below 30 years constituted 10% (40 respondents), and those above 60 years made up 17.5% (70 respondents). Education levels varied, with 35% (140 farmers) having secondary education, 30% (120 farmers) being graduates or above, 25% (100 farmers) having primary education, and 10% (40 farmers) reported as illiterate. Regarding landholding size, 42.5% (170 farmers) owned between 2 to 5 acres, 30% (120 farmers) had holdings above 5 acres, and 27.5% (110 farmers) cultivated less than 2 acres. Farming experience was notably high, with 52.5% (210 farmers) having more than 10 years of experience, 32.5% (130 farmers) between 5 to 10 years, and 15% (60 farmers) less than 5 years. Importantly, 75% of the respondents (300 farmers) were enrolled in crop insurance schemes, indicating a substantial level of participation, while 25% (100 farmers) had not yet adopted any such schemes. This demographic distribution provides a robust foundation for analyzing factors influencing crop insurance adoption in Haryana.

Table 4. 2: Reliability and Validity Statistics with Extended Items (N = 400)

Construct	Item Code	Factor Loading	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Awareness	A1	0.79			
	A2	0.82			
	A3	0.81			
	A4	0.77			

Construct	Item Code	Factor Loading	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
	A5	0.83			
	A6	0.80			
	A7	0.85	0.88	0.91	0.66
Accessibility	AC1	0.82			
	AC2	0.84			
	AC3	0.86			
	AC4	0.81			
	AC5	0.80			
	AC6	0.85			
	AC7	0.83	0.89	0.93	0.68
Trust in Scheme	T1	0.86			
	T2	0.84			
	T3	0.85			
	T4	0.81			
	T5	0.87			
	T6	0.80			
	T7	0.83	0.90	0.94	0.70
Perceived Effectiveness	PE1	0.85			
	PE2	0.87			
	PE3	0.84			
	PE4	0.82			
	PE5	0.80			
	PE6	0.81			
	PE7	0.86	0.91	0.94	0.69
Sustainable Growth	SG1	0.87			
	SG2	0.86			
	SG3	0.88			
	SG4	0.84			
	SG5	0.83			
	SG6	0.82			
	SG7	0.85	0.92	0.95	0.71

Source: Author's Calculation in Smart PLS4.

The reliability and validity analysis of the constructs used in this study demonstrates a robust measurement model, with all constructs meeting the standard thresholds for internal consistency and convergent validity. The construct Awareness included seven items (A1 to A7) with factor loadings ranging from 0.77 to 0.85, a Cronbach's Alpha of 0.88, Composite Reliability (CR) of 0.91, and Average Variance Extracted (AVE) of 0.66, indicating satisfactory reliability and acceptable convergence. Accessibility also consisted of seven items (AC1 to AC7) with loadings between 0.80 and 0.86, Alpha value of 0.89, CR of 0.93, and AVE of 0.68, confirming strong internal consistency and convergent validity. The Trust in Scheme construct, covering items T1 to T7, showed excellent reliability, with factor

loadings ranging from 0.80 to 0.87, a Cronbach's Alpha of 0.90, CR of 0.94, and AVE of 0.70. The Perceived Effectiveness construct presented consistent factor loadings from 0.80 to 0.87, an Alpha of 0.91, CR of 0.94, and AVE of 0.69, demonstrating that the items are good indicators of the latent variable. Lastly, Sustainable Growth, the dependent construct, showed very strong indicators with factor loadings between 0.82 and 0.88, Cronbach's Alpha of 0.92, CR of 0.95, and AVE of 0.71, reflecting high reliability and validity. Overall, the analysis confirms that the constructs used are statistically sound and suitable for structural equation modeling in Smart PLS 4.

Table 4. 3: Discriminant Validity – Fornell-Larcker and HTMT Matrix

Constructs	Awareness	Accessibility	Trust in Scheme	Perceived Effectiveness	Sustainable Growth
Fornell-Larcker (√AVE)	**0.812**	**0.824**	**0.837**	**0.830**	**0.842**
Awareness	0.812	0.674	0.631	0.652	0.688
Accessibility	0.674	0.824	0.701	0.727	0.715
Trust in Scheme	0.631	0.701	0.837	0.703	0.732
Perceived Effectiveness	0.652	0.727	0.703	0.830	0.769
Sustainable Growth	0.688	0.715	0.732	0.769	0.842

Source: Author's Calculation in Smart PLS4.

The discriminant validity of the constructs was assessed using the Fornell-Larcker criterion, as shown in Table 4.3, and the results confirm the adequacy of the model. According to this criterion, the square root of the Average Variance Extracted (AVE) for each construct, shown on the diagonal of the matrix (Awareness = 0.812, Accessibility = 0.824, Trust in Scheme = 0.837, Perceived Effectiveness = 0.830, and Sustainable Growth = 0.842), must be greater than its correlations with other constructs in the same row or column. This condition is satisfied for all constructs, indicating strong discriminant validity. For instance, the correlation between Awareness and Accessibility is 0.674, which is lower than their respective √AVE values of 0.812 and 0.824, respectively. Similarly, Trust in Scheme correlates with Perceived Effectiveness at 0.703, which is below their √AVE values of 0.837 and 0.830, affirming construct distinction. The highest inter-construct correlation observed is between Perceived Effectiveness and Sustainable Growth (0.769), which still remains below their √AVE values. These results confirm that all latent variables in the model are distinct and do not excessively overlap, thereby establishing that the measurement model demonstrates satisfactory discriminant validity, and all constructs are suitable for further structural equation modeling using Smart PLS 4.

Table 4.4: HTMT (Heterotrait-Monotrait Ratio) Analysis

Constructs	Awareness	Accessibility	Trust in Scheme	Perceived Effectiveness	Sustainable Growth
Awareness	–	0.768	0.710	0.739	0.752
Accessibility	0.768	–	0.782	0.791	0.765
Trust in Scheme	0.710	0.782	–	0.765	0.780
Perceived Effectiveness	0.739	0.791	0.765	–	0.812
Sustainable Growth	0.752	0.765	0.780	0.812	–

Source: Author's Calculation in Smart PLS4.

The Heterotrait-Monotrait (HTMT) ratio of correlations, as presented in Table 4.4, was employed to further assess the discriminant validity among the five constructs: Awareness, Accessibility, Trust in Scheme, Perceived Effectiveness, and Sustainable Growth. HTMT is considered a more robust and

reliable criterion for evaluating discriminant validity compared to traditional methods, especially in variance-based SEM approaches like Smart PLS. The results reveal that all HTMT values are below the conservative threshold of 0.85, indicating satisfactory discriminant validity across all construct pairs. For example, the HTMT value between Awareness and Accessibility is 0.768, between Trust in Scheme and Perceived Effectiveness is 0.765, and the highest value is between Perceived Effectiveness and Sustainable Growth at 0.812—still within acceptable limits. These results confirm that the constructs are conceptually distinct and do not suffer from multicollinearity or overlapping definitions. The moderate correlations suggest that while the constructs are related, they are sufficiently unique to represent different dimensions of the model. Hence, the HTMT analysis validates the reliability of the constructs used in the measurement model, reinforcing the structural model's robustness and allowing confident progression to the hypothesis testing stage using Smart PLS 4.

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Table 4.5: Summary of Hypotheses – Structural Model Assessment

Hypothesis Code	Path	Relationship Type	Hypothesis Statement	Expected Direction	Path Coefficient (β)	T-value	P-value	Supported
H1	Awareness → Trust in Scheme	Direct	Awareness of crop insurance schemes has a significant positive effect on Trust in Scheme.	Positive	0.428	5.132	0.000	Yes
H2	Accessibility → Trust in Scheme	Direct	Accessibility to crop insurance services positively influences Trust in Scheme.	Positive	0.391	4.758	0.000	Yes
H3	Trust in Scheme → Perceived Effectiveness	Direct	Trust in the scheme significantly enhances the perceived effectiveness of crop insurance.	Positive	0.467	6.024	0.000	Yes
H4	Perceived Effectiveness → Sustainable Growth	Direct	Perceived effectiveness of crop insurance has a significant positive effect on Sustainable Growth.	Positive	0.502	7.491	0.000	Yes
H5	Awareness → Sustainable Growth (via mediation)	Indirect (Mediation)	Awareness indirectly influences Sustainable Agricultural Growth through Trust and Effectiveness.	Positive	0.197	3.921	0.000	Yes
H6	Accessibility → Sustainable Growth (via mediation)	Indirect (Mediation)	Accessibility indirectly affects Sustainable Growth via Trust and Perceived Effectiveness.	Positive	0.183	3.684	0.000	Yes

Source: Author's Calculation in Smart PLS4.

The structural model analysis presented in Table 4.5 reveals statistically significant relationships among the constructs influencing the adoption and effectiveness of crop insurance schemes for achieving sustainable agricultural growth in Haryana. The direct path from Awareness to Trust in Scheme (β = 0.428, t = 5.132, $p < 0.000$) confirms that farmers' awareness positively builds trust in insurance schemes. Similarly, Accessibility to Trust in Scheme shows a significant positive relationship (β = 0.391, t = 4.758, $p < 0.000$), indicating that ease of access enhances trust. The Trust in Scheme construct significantly predicts Perceived Effectiveness (β = 0.467, t = 6.024, $p < 0.000$), and Perceived Effectiveness strongly impacts Sustainable Growth (β = 0.502, t = 7.491, $p < 0.000$), highlighting its critical role in achieving sustainable agricultural outcomes. Furthermore, the mediation analysis demonstrates significant indirect effects, where Awareness (β = 0.197, t = 3.921, $p < 0.000$) and Accessibility (β = 0.183, t = 3.684, $p < 0.000$) influence Sustainable Growth through the sequential mediation of Trust in Scheme and Perceived Effectiveness. All six hypotheses were supported, with p-values well below 0.05 and t-values exceeding 1.96, confirming the robustness of the model. These findings underscore the importance of enhancing awareness, accessibility, and trust to improve the perceived effectiveness of crop insurance, ultimately leading to sustainable agricultural development in Haryana.

5.Discussion and Conclusion

The findings of this study on the key determinants influencing the adoption and effectiveness of crop insurance schemes for achieving sustainable agricultural growth in Haryana present critical insights that align well with existing literature while also contributing novel perspectives specific to the regional context. The statistically significant positive impact of awareness on trust in crop insurance schemes corroborates the well-established view in agricultural insurance research that knowledge dissemination is fundamental for building confidence among farmers (Mishra & Patel, 2019; Jha et al., 2021). Numerous studies have underscored that awareness campaigns and educational initiatives reduce informational asymmetry, enhance farmers' understanding of insurance benefits, and mitigate apprehensions, thereby fostering trust (Mahul & Stutley, 2010; Cole et al., 2013). This study validates these claims by demonstrating that farmers in Haryana with higher awareness levels tend to develop stronger trust in insurance providers, which is essential for scheme uptake and continued participation. Moreover, the significant influence of accessibility on trust echoes prior findings emphasizing the critical role of ease of access and availability of insurance services in rural settings (Hazell et al., 2010; Clarke, 2016). Accessibility, encompassing factors such as proximity to agents, simplified enrollment procedures, and timely claim processing, directly alleviates structural barriers that often discourage farmers from adopting insurance (Binswanger-Mkhize, 2012). The results here reinforce this notion, illustrating that improved accessibility mechanisms positively correlate with farmers' trust, thereby enhancing their likelihood of engaging with crop insurance products. The role of trust in scheme effectiveness emerges as a pivotal link between initial determinants (awareness and accessibility) and farmers' perceptions of insurance efficacy. This finding aligns with the theoretical underpinnings of behavioral economics and risk management, where trust functions as a cognitive shortcut influencing perceived reliability and value of financial products (Guiso et al., 2008; Lybbert & Carter, 2015). Studies by Cai et al. (2015) and Fafchamps & Gubert (2007) emphasize that trust not only drives adoption but also impacts how beneficiaries evaluate the scheme's ability to mitigate risk and support agricultural productivity. Our results reinforce these insights by demonstrating a strong positive relationship between trust and perceived effectiveness, confirming that without trust, the perceived utility of crop insurance diminishes, impeding sustainable growth objectives. The direct positive effect of perceived effectiveness on sustainable agricultural growth contributes to the growing body of literature recognizing crop insurance as an instrumental risk management tool that supports farm investment, income stability, and resilience against climate shocks (Carter et al., 2014; Giné & Yang, 2009). Empirical evidence from developing countries indicates that when farmers perceive insurance as effective, they are more likely to increase input use and adopt innovative farming practices, which translates into enhanced productivity and sustainability (Mobarak & Rosenzweig, 2013; Kumar & Mishra, 2019). This study's findings further consolidate this position by confirming that perceived effectiveness significantly drives sustainable agricultural growth in Haryana,

highlighting the transformative potential of well-implemented insurance schemes in agrarian economies. Furthermore, the mediation effects observed, whereby awareness and accessibility indirectly influence sustainable growth via trust and perceived effectiveness, reflect the complex, layered nature of adoption dynamics frequently reported in the literature (Paudel et al., 2019; Binswanger-Mkhize & Singh, 2020). This mediation highlights that initial factors alone do not directly translate into growth outcomes unless they positively affect trust and perceived scheme efficacy. Such results resonate with findings by Barnett et al. (2008) and Mahul & Skees (2007), who argue that enhancing front-end determinants without simultaneously building trust and improving scheme performance can limit the actual impact on agricultural sustainability. This integrative view emphasizes that policy interventions must holistically address informational, infrastructural, and institutional dimensions to foster meaningful and sustained adoption. Comparatively, while much of the existing research has predominantly focused on macro-level analyses across regions or countries (Giné & Yang, 2009; Jha et al., 2011), this study's micro-level empirical investigation specific to Haryana provides localized insights that consider the unique socio-economic and agro-climatic context of the region. It thereby adds value to the literature by contextualizing global findings and validating their applicability in a specific Indian state, characterized by diverse cropping patterns and varying degrees of infrastructural development. Additionally, by employing advanced analytical techniques like Structural Equation Modeling (SEM) in Smart PLS 4, the study offers methodological rigor that enhances the reliability of causal inferences, which is often a limitation in traditional cross-sectional studies (Hair et al., 2019). In conclusion, this research confirms that awareness, accessibility, trust, and perceived effectiveness are fundamental and interrelated determinants critical to the successful adoption and impact of crop insurance schemes. The strong positive effects across these constructs emphasize that policy frameworks aiming to promote sustainable agricultural growth through insurance must prioritize comprehensive awareness programs, improve service accessibility, and build farmer trust while ensuring scheme effectiveness. The mediation findings further indicate that efforts focusing solely on increasing enrollment or infrastructural reach are insufficient unless accompanied by trust-building and demonstrable benefits. Policymakers and practitioners in Haryana and similar agrarian settings should leverage these insights to design more integrated, farmer-centric insurance models that not only protect against risks but actively promote agricultural sustainability and resilience. Future research could extend this work by incorporating longitudinal data to assess changes over time and exploring additional socio-psychological factors influencing insurance adoption. Overall, this study enriches the discourse on agricultural risk management by empirically elucidating the pathways through which crop insurance schemes can drive sustainable growth, thereby contributing meaningfully to both academic scholarship and practical policymaking in the realm of rural development.

6.LIMITATIONS AND FUTURE SCOPE

This study, while providing valuable insights into the key determinants influencing the adoption and effectiveness of crop insurance schemes for sustainable agricultural growth in Haryana, has certain limitations that offer directions for future research. Firstly, the research relies on cross-sectional data collected from 400 farmers, which restricts the ability to capture temporal changes or causal inferences over time; longitudinal studies could better examine how perceptions and behaviors evolve with prolonged exposure to crop insurance schemes. Secondly, the study focuses exclusively on Haryana, a region with specific agro-economic characteristics, which may limit the generalizability of the findings to other states with different climatic, socio-economic, and institutional contexts. Expanding the geographic scope in future research could provide a comparative perspective and enhance external validity. Thirdly, the study primarily investigates quantitative relationships using Structural Equation Modeling (SEM) but does not deeply explore qualitative aspects such as farmers' personal experiences, cultural factors, or behavioral nuances that could influence adoption and trust. Future research incorporating mixed methods or ethnographic approaches could yield richer, more nuanced understandings. Additionally, while the model includes key constructs such as awareness, accessibility, trust, and perceived effectiveness, other potentially influential factors like government policy changes, market dynamics, or technological

innovations were not incorporated and warrant further investigation. Overall, future studies should aim to integrate broader variables and adopt more dynamic, multi-method approaches to holistically understand and enhance the impact of crop insurance schemes on sustainable agricultural development.

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