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# DETERMINANTS OF TECHNOLOGY ADOPTION UNDER THE FARMER FIRST PROGRAMME: EVIDENCE FROM MID-HILL REGIONS OF UTTARAKHAND, INDIA

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**ABSTRACT**

Technology adoption under the Farmer FIRST Programme implemented by GBPUA&T, Uttarakhand, remains uneven despite continuous interventions. The decision to adopt technologies is influenced by a combination of interpersonal, economic, psychological, institutional, and community-level factors. Understanding the factors influencing technology adoption among beneficiaries is crucial to generating evidence to design extension programmes that support informed decision-making in the future. The study was conducted in three villages Jeoli, Syalikhet, and Dogra using a descriptive research design. The villages were selected purposively, and a total of 138 FFP beneficiaries were selected proportionately based on Cochran's formula, using the official programme records. Data were collected through a pre-tested interview schedule and analysed using frequency, percentage, range, mean, standard deviation, correlation, partial correlation controlling for education, chi-square tests, multiple regression and t-test of significance. The majority of beneficiaries (65.21%) demonstrated a medium level of technology adoption (Mean = 45.35, SD = 6.22). Innovativeness emerged as the dominant predictor, followed by attitude towards livelihood. Partial correlation analysis confirmed that all six predictors retained significant, independent of education, while the regression model explained approximately 27% of the variation in technology adoption. In contrast, variables like age, income, and landholding were non-significant, suggesting that when financial access barriers are overcome, adoption is governed by psychological readiness rather than resource endowment. The findings highlight the need for farmer-centric extension strategies that strengthen behavioural attributes alongside technology dissemination. The study provides useful evidence for policymakers, extension professionals, and programme planners to design location-specific interventions that enhance technology adoption and improve the effectiveness and sustainability of future Farmer FIRST Programme initiatives.
***Keywords*:** Technology adoption; Farmer FIRST Programme; Behavioural determinants; Innovativeness; Participatory extension; livelihood diversification.

## Introduction

Agriculture remains the backbone of India's rural economy, employing nearly 46.1% of the country's workforce and contributing approximately 18-19% to national Gross Value Added (GVA) (PIB, GOI, 2025). Over the past several decades, Indian agriculture has transitioned into one of the world's largest agricultural producers through sustained investments in scientific research, irrigation infrastructure, input intensification, technology and institutional reforms. Yet this transformation remains uneven, particularly in ecologically fragile regions such as the mid-hills of Uttarakhand, where small and fragmented landholdings, limited market connectivity, and the progressive feminisation of agriculture pose distinct developmental challenges.

These intersecting ecological, economic and demographic pressures have intensified concerns regarding livelihood sustainability, technology stagnation and climate vulnerabilities in the mid-hills regions of Uttarakhand. In such contexts, the adoption of contextually appropriate agricultural technologies remains critical for enhancing productivity, sustainability and increased adaptive capacity among farmers. The literature on agricultural technology adoption has evolved considerably from linear and economically deterministic models to socially embedded and behaviourally mediated processes. Technology adoption is shaped by the interaction of psychological dispositions, institutional environments, social networks, cultural norms and any perceived risk (Rogers, 2003; Bandiera and Rasul, 2006; Meijer *et al.*, 2015). Farmers today are not passive recipients of externally generated technologies, but active evaluators of innovations in relation to their livelihood aspirations, resource constraints, prior experiences, and community expectations.

In response to this evolution in the analytical ability of farmers, the Indian Council of Agricultural Research (ICAR), operating through 113 research institutes and a network of 731 Krishi Vigyan Kendras (KVKs), launched the Farmer FIRST Programme (FFP) in 2016 as a flagship participatory extension initiative. The programme explicitly positions farmers as active partners in the research-extension continuum: generating problems from field realities, co-designing solutions, and providing feedback that shapes subsequent technology generation. By facilitating direct farmer–scientist interaction, on-farm experimentation, and location-specific solutions, FFP aspires to bridge the persistent gap between laboratory innovations and field-level adoption.

Despite the expanding operational footprint of the Farmer FIRST Programme across multiple agro-ecological regions of India, systematic empirical evidence regarding the socio-psychological and institutional correlates of adoption within the programme remains limited. Existing studies on FFP have largely focused on programme implementation, beneficiary profiling, or descriptive impact assessments, with comparatively limited attention to the behavioural mechanisms underlying adoption decisions. While many interventions have already been organised under FFP, a critical gap exists in our understanding of the actual adoption rates and the success of these interventions in real-world scenarios. The impact of existing extension interventions remains partially or incompletely assessed, hindering our ability to fine-tune and optimise these programs for maximum impact. This is particularly concerning given the complex interplay of factors influencing technology adoption, which spans interpersonal, economic, psychological, institutional, and community levels. The technology developer should incorporate the needs and perceptions of farmers during the stages of technology design and development to enhance the easy adoption of technology.

As ICAR's flagship extension program, FFP's success largely depends on understanding how widely and effectively farmers adopt these technologies. Adoption studies serve as essential tools to evaluate the program's significance for the farming community, providing insights into the varied characteristics and barriers influencing farmers' adoption of agricultural innovations. By examining adoption constraints and variability, it becomes possible to tailor interventions to farmers' needs, building a robust strategy to enhance the extension system. Adoption will help us understand the heterogeneous characteristics concerning the extent of adoption among farmers. Even the adoption of appropriate agricultural technology holds the key to development.

The Farmer FIRST Programme is also implemented by G. B. Pant University, among the other 52 FFP-implementing institutes of ICAR. Under FFP, the University is working in the mid-hills, covering three villages in Uttarakhand, mainly in the Bhimtal block of the Nainital district. The villages are Dogara, Syalikhet and Jeoli. GBPUA&T implemented the project entitled "Enhancing livelihood opportunities of the farming community in mid-hills of Uttarakhand" under the Farmer FIRST Programme. G.B. Pant University undertook three modules during this project. Among them were horticulture-based, livestock-based, and enterprise-based modules that suit different locales under consideration. The project focused on increasing sustainability in farmers' income, enhancing livelihood opportunities, and empowering women of the mid-hills.

The mid-hill regions of Uttarakhand provide a particularly important setting for examining the dynamics of technology adoption under participatory extension systems. Small and fragmented holdings, difficult terrain, limited infrastructural connectivity, and highly heterogeneous livelihood systems create conditions in which conventional standardised extension models often prove inadequate (Rasul and Hussain, 2015). In this context, the institution's project members play a vital role in prioritising the problems of the villagers and identifying appropriate solutions by involving farmers as participants and partners in developing project objectives. Implementing the Farmer FIRST Programme by G. B. Pant University aligns with and prioritises objectives laid down by ICAR during the inception of FFP.

The study investigates the factors associated with technology adoption among Farmer FIRST Programme beneficiaries in the mid-hill region of Uttarakhand. Specifically, the study aims to: (i) examine the socio-economic, communication, and psychological profile of FFP beneficiaries; (ii) assess the extent of technology adoption by the beneficiaries of the Farmer FIRST Programme; (iii) analyse the relationship between selected behavioural, attitudinal, and institutional variables and adoption outcomes using correlation and multivariate statistical techniques; and (iv) identify the relative contribution of significant predictors to adoption behaviour. By situating technology adoption within the broader framework of participatory rural transformation and behavioural extension theory, the study seeks to contribute to emerging debates on farmer-centred innovation systems and the future of agricultural extension in ecologically vulnerable mountain regions.

## Review of Literature

A review of relevant literature is undertaken to understand the existing knowledge and identify research gaps related to technology adoption under the Farmer FIRST Programme. The literature is systematically organised to situate the present study within the available body of knowledge.

### (a) Personal, socio-economic, psychological and communication characteristics of the beneficiaries

Recent studies under FFP and allied KVK intervention have reported beneficiaries as predominantly middle-aged, marginal to small farmers with moderate exposure to extension and mass-media channels. Khan *et al*. (2020) revealed that the majority of farmers were from the middle age group (47.50%), had completed high school and above (53.33%), and had small land holdings of 1-2 hectares (52.50%). Material possessions were also low, with 38.33% of farmers reporting this. In terms of psychological attributes, farmers showed medium levels of economic motivation (40.83%), scientific orientation (40.83%), and high innovation proneness (45.83%). Furthermore, both communication attributes indicated high mass media exposure and contact with development agencies (42.50%). Harshavardhan *et al.* (2024), concluded that the majority of beneficiaries (71.67%) were middle-aged and had completed middle school education (20.83%). Most were marginal farmers (42.50%) with a medium level of farming experience (71.67%). Additionally, a significant proportion had undergone a medium level of training (66.67%), had a medium level of extension contact (44.17%), a medium level of social participation (57.50%), and a moderate level of mass media exposure (75%). Farmers exhibited a medium level of extension orientation (62.50%) and scientific orientation (59.17%). These findings suggest that beneficiaries possess communication and behavioural attributes that can facilitate technology adoption, although variations in socio-economic characteristics continue to influence the effectiveness of extension interventions across different locations.

### (b) Extent of technology adoption by the beneficiaries of the Farmer FIRST Programme

The pattern of technology adoption reported in the recent literature is more practice-specific rather than uniform. Jadoun *et al.* (2023) indicated that a significant proportion of farmers exhibited a high level of adoption (69.33%) of kitchen gardening practices, followed by a medium level of adoption (27.33%) and only 3.33% of farmers were classified under a low level of adoption. The net adoption rate of kitchen gardening among beneficiaries was reported at 88%. Sharma *et al*. (2024) revealed that the majority of them adopted the complete management of paddy residue (49.25%), followed by those who did not adopt any techniques (25.67%) and then those who partially adopted the residue management techniques (25.07%) for paddy. Thangjam *et al*. (2024) reported that the majority of respondents (64.38%) had a medium level of adoption, followed by a high level of adoption (19.69%) and a low level of adoption (25.93%). Collectively, these studies indicate that adoption is shaped by the nature of the practice (input-based versus management -based) and by the intensity of follow-up extension support. That is a very distinct part of the present study on the FFP technology adoption that seeks to discover.

### (c) Relationship between the beneficiaries' personal, socio-economic, psychological and communication characteristics and the extent of technology adoption

The trend of correlational studies shows a positive significant relationship between technology adoption and variables such as extension contact, scientific orientation, attitude and training exposure, whereas age shows a negative and non-significant relationship. Rutsa and Jha (2023) found that formal information sources, extension contact, scientific orientation, training exposure, and attitude had positive and significant correlations with the extent of technology adoption by respondents at the 1% level of probability. Age, mass media, and market orientation had negative and significant correlations at the (5%) and (1%) levels of probability. Meanwhile, sex, family size, education, size of total land holding (acre), size of land holding under SRI, annual income, income from paddy cultivation, informal sources, and social participation had non- significant correlations with the extent of technology adoption by the respondents. Lal *et al.* (2025), in a study, indicated that when Multinomial logistic regression was used to identify factors influencing adoption of Integrated Pest Management. Then, findings revealed that factors significantly influencing adoption of IPM with (5%) significance level were age, education, extension contact and cosmopoliteness, while social participation was also found to be significant at (10%) level. The study also underscored the importance of specific interventions and educational programs to promote the adoption of sustainable agricultural practices. Taken together, it indicates that behavioural and institutional factors play a more influential role than demographic characteristics in shaping technology adoption, pointing to the importance of strengthening extension interventions and farmers' capacity building to increase the adoption of agricultural technology.

**(d) Relative contribution of significant predictors to adoption behaviour.**

The studies that move beyond simple correlation to quantify the relative or marginal contribution of predictors remain comparatively limited in the FFP literature, making the study's multivariate work particularly relevant to the fourth objective. Pandeya *et al.* (2025) revealed that old-aged farmers are less likely to adopt new technologies, with each additional year of their age decreasing the chances of adoption by 8%. Furthermore, farming experience and farm size owned increase the likelihood of adoption by 4% and 3%, respectively. Meanwhile, factors like gender, income, education and prior expertise were not significant predictors. This approach helps identify the effect and contribution of the individual variable net of the others. The approach that the present study intends to apply to behavioural, attitudinal, and institutional variables among FFP beneficiaries. Venkatesan *et al.* (2023), in a multi-locational assessment of the farmer FIRST Programme conducted across different agro-ecological zones of India for understanding how FFP is aligned with SDGs, demonstrated that the magnitude of programme impact varies systematically with different zones and institutions undertaking it. It is not at all uniform across all 52 FFP institutions, reinforcing the argument that the strength of individual predictors of adoption and impact under FFP cannot be generalised and must be empirically found out for each study area.

## Theoretical Framework

The present study is anchored in a multidisciplinary theoretical foundation that integrates three complementary traditions: (i) Diffusion of Innovations Theory, (ii) the Theory of Planned Behaviour, and (iii) the Unified Theory of Acceptance and Use of Technology, supplemented by empirical determinants identified in agricultural extension literature.

### *Diffusion of Innovations Theory (Rogers, 2003)*

Rogers' Diffusion of Innovations theory provides the foundational macro-level framework for understanding how agricultural technologies propagate through a social system over time. The theory identifies five innovation attributes relative advantage, compatibility, complexity, trialability, and observability that shape farmers' perceptions and determine both the rate and pattern of adoption. In hill agriculture contexts such as Uttarakhand, where socio-economic heterogeneity and ecological diversity are pronounced, diffusion processes are characteristically uneven, shaped by local knowledge systems, peer learning dynamics, and the depth of institutional interactions. The Farmer FIRST Programme directly aligns with diffusion principles by embedding farmer participation, on-farm experimentation, and iterative feedback mechanisms into its operational design, enhancing the observability and trialability of promoted technologies.

### *Theory of Planned Behaviour (Ajzen, 1991)*

The Theory of Planned Behaviour (TPB) offers a micro-level behavioural account of adoption by positing that behaviour is determined by intention, which is itself shaped by three constructs: (a) attitude towards the behaviour: the farmer's appraisal of whether adopting a technology will yield positive outcomes; (b) subjective norms: the perceived social pressure from peers, family, and extension agents; and (c) perceived behavioural control: the degree to which the farmer feels capable of performing the behaviour given their resources and knowledge. In the present study, attitude towards livelihood diversification operationalises the attitudinal construct, while innovativeness and risk orientation capture dimensions of behavioural disposition and subjective control.

### *Unified Theory of Acceptance and Use of Technology (UTAUT — Venkatesh et al., 2003)*

The UTAUT model enriches the analysis by identifying four core determinants of technology acceptance: performance expectancy (belief that the technology will improve productivity), effort expectancy (perceived ease of use), social influence (peers and extension agents encouraging adoption), and facilitating conditions (availability of institutional and infrastructural support). In the FFP context, contact with the project team captures both social influence and facilitating conditions; scientific orientation aligns with effort and performance expectancy; economic motivation corresponds directly to performance expectancy.

### *Integrated Conceptual Framework*

The study synthesises these three theoretical traditions into an integrated framework that conceptualises technology adoption as the product of four interacting variable clusters: (a) socio-economic characteristics (age, education, landholding, income); (b) psychological attributes (innovativeness, economic motivation, scientific orientation, risk orientation); (c) attitudinal disposition (attitude towards livelihood diversification); and (d) communication behaviour (contact with extension professionals). This framework is visually represented in Figure 1 of the original paper and provides the analytical scaffold for the correlation, partial correlation, and regression analyses reported herein.

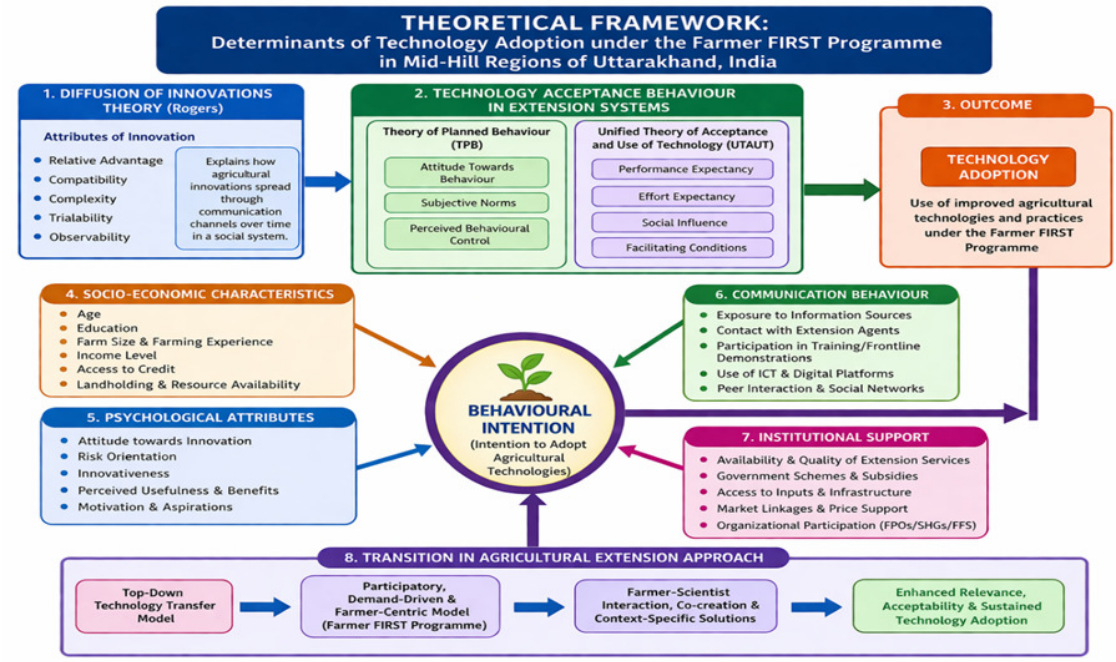


**Fig. 1:** Integrated Conceptual Framework Determinants of Technology Adoption under the Farmer FIRST Programme (Source: Author's representation integrating Rogers, 2003; Ajzen, 1991; Venkatesh *et al*., 2003)

## Materials and Methods

### Study Area, Universe, and Sampling

The study was conducted in Bhimtal block of Nainital district, Uttarakhand, a mid-hill agro-ecological zone located between 1,300–2,000 m above sea level. Three villages Dogra, Jeoli, and Syalikhet were purposively selected from the official FFP roster based on programme maturity (more than three years of active implementation) and agro-ecological representativeness; each village corresponds to a distinct FFP enterprise intervention (livestock and vegetable integration in Dogra, apiculture and honey processing in Jeoli, and backyard poultry in Syalikhet). The total FFP beneficiary population across the three villages comprised 210 registered households. Sample size was determined using the Cochran (1977) formula at a 95% confidence level and ±5% precision, yielding n = 138, with village-wise proportional allocation ($n_i = (N_i/N) \times n$). Data were collected through a structured, pre-tested interview schedule administered through personal interviews during January–April 2025.

### Variables and Measurement

The study examined 14 independent variables spanning three domains. Socio-economic variables included age, sex, education, size of landholding (in nali), occupation, annual income (Rs.), livestock possession, and material possession. Communication behaviour was captured through contact with the project team. Psychological and attitudinal variables comprised innovativeness (Jaussi and Dionne, 2003; 6 items), attitude towards livelihood diversification (Reddy *et al*., 2020; 8 items), economic motivation (Meena and Fulzele, 2008; 8 items), scientific orientation (Supe, 2007; 6 items), and risk orientation (Padaria *et al*., 2017; 19 items). All psychological scales used five-point Likert-type response formats, with Cronbach's α ranging from 0.75 to 0.88. The dependent variable, extent of technology adoption, was measured through a composite index across all FFP-promoted technologies, scored on a three-point scale (fully adopted = 3, partially adopted = 2, not adopted = 1) and summed to produce a continuous adoption index (Mean = 45.35, SD = 6.22), with beneficiaries categorised as low (<39.12), medium (39.12–51.58), or high (>51.58) adopters using mean ± SD cut-offs.

**Data Quality and Ethical Consideration**

As the achieved sample (n = 138) matched the proportionally allocated target exactly, no refusals or respondent replacements occurred during data collection. All 14 independent variables and the adoption index were fully completed for 138 respondents; one respondent had a missing value on contact with the project team, reducing the usable sample for analyses involving that variable to n = 137 (reported accordingly in Sections 5.4–5.7). Cook's distance was used to screen the regression sample for overly influential cases: the maximum observed value (0.09) was well below the conventional concern threshold of 1.0, and no adoption scores exceeded 3 standard deviations from the mean, so no cases were removed as outliers.

**Statistical Analysis**

The analysis proceeded in stages, frequencies, percentages, means, standard deviations, coefficients of variation, and standard errors were first computed to characterise the sample and the distribution of each variable. Relationships between beneficiary characteristics and the extent of technology adoption were then examined using Pearson's product-moment correlation, with the t-test applied to judge significance at the 5% and 1% levels; because sex is dichotomous and occupation is a nominal three-category variable, these two were tested through point-biserial correlation and one-way analysis of variance, respectively, rather than forced into the Pearson framework. Effect sizes were interpreted against Cohen's (1988) conventions, treating coefficients below 0.1 as negligible, 0.1 to 0.3 as small, 0.3 to 0.5 as medium, and above 0.5 as large, and 95% confidence intervals for the significant coefficients were obtained through Fisher's Z-transformation.

Since education may influence both psychological characteristics and technology adoption, partial correlation analysis was performed to determine whether the observed relationships remained significant after controlling for the effect of education. The variables that survived the bivariate stage were then entered together into a multiple linear regression on the adoption index, allowing their joint explanatory power to be estimated net of the variance they share with one another. The adequacy of this model was verified before interpretation: variance inflation factors were inspected for multicollinearity, residual normality was tested with the Shapiro–Wilk statistic, homoscedasticity with the Breusch–Pagan test, and independence of errors with the Durbin–Watson statistic; where the homoscedasticity assumption was found wanting, heteroscedasticity-robust standard errors were estimated alongside the classical ones so that conclusions rest only on results stable under both. All computations were carried out in Python using the pandas, scipy.stats, and statsmodels libraries, which implement the same estimators as standard statistical packages such as SPSS and R and yield identical results for these procedures.

## Results and Discussion

***Socio-Economic and Psychological Profile of FFP Beneficiaries***

The distribution of beneficiaries across all fourteen independent variables is presented below, along with the frequency and percentage distribution

**Table 1:** Distribution of Beneficiaries by Age, Education, Landholding, Income, and Psychological–Communication Attributes (n = 138)

| Variable | Category | Frequency | Percentage (%) |
|---|---|---|---|
| Age (Mean=46.42, SD=10.01) | Young (<36 yrs) | 22 | 15.94 |
| | Middle (36–56 yrs) | 91 | 65.94 |
| | Old (>56 yrs) | 25 | 18.12 |
| Education | Illiterate | 19 | 13.76 |
| | Primary / Middle School | 60 | 43.47 |
| | High School / Intermediate | 36 | 26.07 |
| | Graduation and above | 23 | 16.67 |

| | | | |
|---|---|---|---|
| Landholding (1 nali = 0.02 ha) | Low (<30 nali) | 129 | 93.47 |
| | Medium (31–60 nali) | 7 | 5.07 |
| | High (>60 nali) | 2 | 1.44 |
| Annual Income (Rs.) | Low (<1,70,000) | 122 | 88.41 |
| | Medium (1,70,001–3,35,000) | 8 | 5.80 |
| | High (>3,35,000) | 8 | 5.80 |
| Contact–Project Team (Mean=7.00, SD=1.556) | Low (<5.44) | 12 | 8.71 |
| | Medium (5.44–8.55) | 112 | 81.15 |
| | High (>8.55) | 14 | 10.14 |
| Innovativeness (Mean=8.18, SD=1.19) | Low (<6.98) | 9 | 6.52 |
| | Medium (6.98–9.38) | 114 | 82.60 |
| | High (>9.38) | 15 | 10.88 |
| Attitude–Livelihood Div. (Mean=55.13, SD=5.43) | Less favourable (<49.70) | 17 | 12.31 |
| | Favourable (49.70–60.57) | 100 | 72.46 |
| | More favourable (>60.57) | 21 | 15.23 |
| Economic Motivation (Mean=25.44, SD=3.68) | Low (<21.76) | 14 | 10.14 |
| | Medium (21.76–29.13) | 103 | 74.63 |
| | High (>29.13) | 21 | 15.23 |
| Scientific Orientation (Mean=23.91, SD=2.17) | Low (<21.74) | 11 | 7.97 |
| | Medium (21.74–26.09) | 108 | 78.26 |
| | High (>26.09) | 19 | 13.77 |
| Risk Orientation (Mean=43.21, SD=3.245) | Low (<39.96) | 16 | 11.59 |
| | Medium (39.96–46.45) | 101 | 73.18 |
| | High (>46.45) | 21 | 15.23 |

**Table 1a:** Distribution of Beneficiaries by Sex and Occupation (n = 138)

| Variable | Category | Frequency | Percentage (%) |
|---|---|---|---|
| Sex | Male | 59 | 42.75 |
| | Female | 79 | 57.25 |
| Occupation | Agriculture and allied sector | 102 | 73.91 |
| | Agriculture and job | 28 | 20.28 |
| | Agricultural labour | 8 | 5.81 |

**Table 1b:** Distribution of Beneficiaries by Livestock Possession (n = 138)

| No. of Livestock Owned | Frequency | Percentage (%) |
|---|---|---|
| 0 | 15 | 10.90 |
| 1 | 41 | 29.71 |
| 2 | 42 | 30.43 |
| 3 | 32 | 23.18 |
| 4 | 4 | 2.89 |
| 5 | 4 | 2.89 |

*Species-wise (multiple responses permitted): Cows 55.79%, Buffaloes 47.10%, Chicken 40.57%, Goat 30.43%, Fish 3.62%, Ducks 2.89%, Pigs 2.89%, Other 2.89%.*

**Table 1c:** Distribution of Beneficiaries by Material Possession (n = 138; multiple responses)

| Category | Item | Percentage (%) |
|---|---|---|
| Agricultural implements | Spade | 86.95 |
| | Tractor | 44.20 |
| | Sprayer | 38.40 |
| | Khurpi | 33.33 |
| | Plough | 15.21 |
| | Sickle | 12.31 |
| | Harrow | 5.07 |
| | Bullock cart | 2.17 |
| | Tube well | 1.44 |
| Transport | Motorcycle | 35.50 |

| | | |
|---|---|---|
| | Scooter | 11.59 |
| | Car | 7.24 |
| | Bicycle | 3.62 |
| Mass-media / communication | Mobile phone | 99.27 |
| | Television | 73.91 |
| | Internet | 58.69 |
| | Radio | 2.17 |

The beneficiary profile reveals that middle-aged beneficiaries predominate (65.94%, Mean age = 46.42 years), which is consistent with well-documented patterns of youth out-migration in the hills. Additionally, the disproportionately high percentage of female beneficiaries (57.25%) is consistent with the FFP's intentional targeting of women farmers, especially in Syalikhet. In this context, hill agriculture is marginal and subsistence-oriented, as evidenced by the near-total concentration of beneficiaries in the low landholding category (93.47%, <30 nali) and the correspondingly high share reporting low annual income (88.41%). This is consistent with the dominance of agriculture and related occupations (73.91%) over agricultural labour (5.81%). Adoption decisions are made in a resource-constrained environment, as evidenced by the small and concentrated livestock holdings (one to three animals for 83.32% of beneficiaries, mostly cows and buffaloes) and the skewed material possession toward low-cost hand tools and mobile telephony (spade 86.95%, mobile phone 99.27%) rather than mechanised or motorised assets.

Psychologically, most beneficiaries clustered in the medium category across innovativeness (82.60%), attitude towards livelihood diversification (72.46% favourable), economic motivation (74.63%), scientific orientation (78.26%), risk orientation (73.18%), and extension contact (81.15%). This convergence around the medium/favourable band, rather than the low or high extremes, is consistent with a beneficiary population whose attitudinal readiness has been raised above baseline by sustained participatory engagement, while a smaller high-scoring segment (10–15% across most psychological variables) represents a potential pool of lead farmers for peer diffusion.

### *Extent of Technology Adoption*

**Table 2:** Distribution of Beneficiaries by Extent of Technology Adoption (n = 138)

| S.No. | Category | Score Range | Frequency | Percentage (%) |
|---|---|---|---|---|
| 1 | Low Adoption | <39.12 | 23 | 16.67 |
| 2 | Medium Adoption | 39.12–51.58 | 90 | 65.21 |
| 3 | High Adoption | >51.58 | 25 | 18.12 |
| | Total | Mean=45.35, SD=6.22 | 138 | 100.00 |

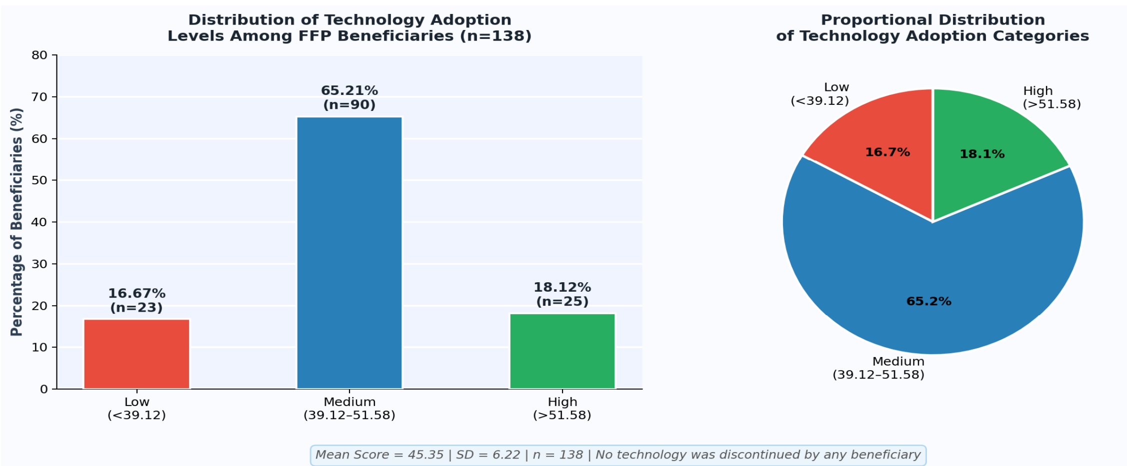


**Fig. 2 :** Distribution of Technology Adoption Levels among FFP Beneficiaries (n = 138)

The majority of FFP beneficiaries (65.21%) recorded a medium level of technology adoption, with 18.12% classified as high adopters and 16.67% as low adopters. This medium-dominant distribution is broadly comparable to other participatory extension programmes in India, including Kaimal and Thomas

(2022), who reported 64% medium adoption in apiculture, and Warshini *et al*. (2022), who found 61% medium adoption for banana production technology. No beneficiary across the three villages reported discontinuing an adopted technology, which is suggestive of, though not conclusive proof of, perceived relevance and contextual fit of the FFP interventions; alternative explanations, such as social-desirability bias in self-reported discontinuation or a short recall window, cannot be ruled out with the present cross-sectional design and should be considered when interpreting this finding.

***Descriptive Statistics of Continuous Variables***

**Table 3:** Descriptive Statistics of Key Continuous Variables (n = 138)

| Variable | Mean | SD | CV (%) | SE | Min | Max |
|---|---|---|---|---|---|---|
| Age (years) | 46.42 | 10.01 | 21.56 | 0.852 | 18 | 72 |
| Contact with Project Team | 7.00 | 1.556 | 22.23 | 0.133 | 3 | 9 |
| Innovativeness | 8.18 | 1.19 | 14.55 | 0.101 | 6 | 12 |
| Attitude–Livelihood Div. | 55.13 | 5.43 | 9.85 | 0.462 | 35 | 72 |
| Economic Motivation | 25.44 | 3.68 | 14.47 | 0.313 | 16 | 36 |
| Scientific Orientation | 23.91 | 2.17 | 9.08 | 0.185 | 18 | 28 |
| Risk Orientation | 43.21 | 3.245 | 7.51 | 0.276 | 34 | 53 |
| Technology Adoption (DV) | 45.35 | 6.22 | 13.72 | 0.530 | 22 | 63 |

*Note: DV = Dependent Variable; CV(%) = Coefficient of Variation; SE = Standard Error.*

The coefficient of variation offers a scale-independent view of relative variability. Scientific orientation (CV = 9.08%) and risk orientation (CV = 7.51%) show the most homogeneous distributions, while age (CV = 21.56%) and contact with the project team (CV = 22.23%) show the greatest relative heterogeneity, reflecting genuine variation in life stage and in the depth of beneficiary extension relationships across the three villages.

***Correlates of Technology Adoption: Pearson Correlation Analysis***

All fourteen independent variables were tested against the adoption index. Pearson's correlation was used for the continuous and count variables, point-biserial correlation for the binary sex variable, and one-way ANOVA for the nominal occupation variable.

**Table 4:** Correlation of Beneficiary Characteristics with Extent of Technology Adoption (n = 138)

| S.No. | Independent Variable | r / F | t / df | Significance & Effect |
|---|---|---|---|---|
| 1 | Age | -0.1359 | t=-1.599 | NS \| Small |
| 2 | Sex (point-biserial) | 0.0683 | t=0.799 | NS \| Negligible |
| 3 | Education | 0.0844 | t=0.981 | NS \| Negligible |
| 4 | Land Holding | 0.0741 | t=0.859 | NS \| Negligible |
| 5 | Occupation (one-way ANOVA) | F=3.245 | df=2,135 | * \| $\eta^2$=0.046 (small) |
| 6 | Annual Income | 0.0335 | t=0.390 | NS \| Negligible |
| 7 | Livestock Possession | 0.0728 | t=0.851 | NS \| Negligible |
| 8 | Material Possession | 0.1700 | t=2.012 | * \| Small |
| 9 | Contact with Project Team | 0.1721 | t=2.037 | * \| Small |
| 10 | Innovativeness | 0.4213 | t=5.489 | ** \| Medium |
| 11 | Attitude–Livelihood Div. | 0.2793 | t=3.392 | ** \| Small |
| 12 | Economic Motivation | 0.1759 | t=2.083 | * \| Small |
| 13 | Scientific Orientation | 0.1744 | t=2.066 | * \| Small |
| 14 | Risk Orientation | 0.2362 | t=2.834 | ** \| Small |

*Note: * $p<0.05$; ** $p<0.01$; NS = Not Significant. Pearson correlations at df=136 (df=135 for Contact with Project Team, which had one missing response); t-tabulated: $t_{0.05}$=1.978, $t_{0.01}$=2.612. Occupation tested via one-way ANOVA (F, df=2,135) with $\eta^2$ as effect size, since it is a nominal three-category variable; sex tested via point-biserial correlation. Effect sizes per Cohen (1988).*

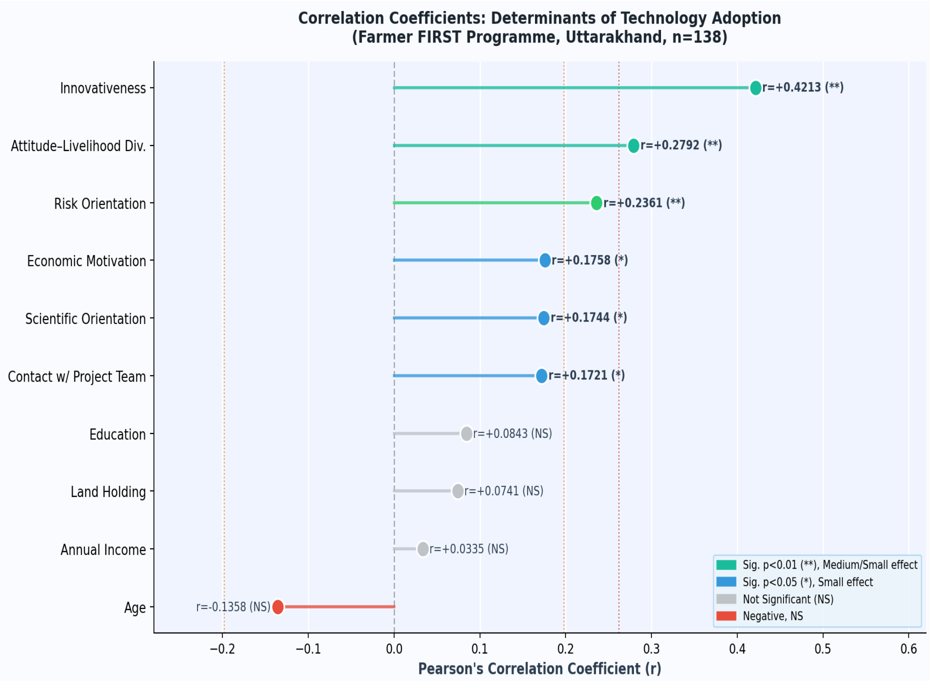


**Fig. 3:** Pearson's Correlation Coefficients: Determinants of Technology Adoption

Among the socio-economic and asset variables, material possession stands out as the only significant correlate of adoption (r = 0.1700, p<0.05). Beneficiaries who owned more agricultural implements, transport, and communication assets recorded somewhat higher adoption, joining contact with the project team, innovativeness, attitude towards livelihood diversification, economic motivation, scientific orientation, and risk orientation as the seventh significant correlate. Occupation also showed a significant, though small, association with adoption ($F(2,135) = 3.245$, $p<0.05$, $\eta^2 = 0.046$): the eight beneficiaries classified as agricultural labourers recorded the highest mean adoption (50.12) relative to those in agriculture-and-allied (44.74) or agriculture-plus-job (46.25) categories, though this group is small (n = 8) and the finding should be treated cautiously. Sex and livestock possession showed no significant association with adoption (r = 0.0683 and 0.0728, respectively, both NS), consistent with the pattern observed for age, education, landholding, and annual income.

According to the correlation analysis, the majority of traditional socio-economic variables: age, sex, education, landholding, annual income, and possession of livestock were not significantly and favourably associated with technology adoption, but psychological, communication-related, and one material-asset variable were. A cross-sectional correlational design cannot rule out reverse causation (e.g., farmers who have already benefited from adoption reporting higher innovativeness) or omitted-variable explanations; this caution is carried through the rest of the discussion. This pattern is consistent with, but does not prove, the interpretation that behavioural readiness and institutional engagement matter more than structural resource endowment once a program removes financial access barriers.

Innovativeness showed the strongest association with adoption (r = 0.4213, p<0.01), the only variable to reach a medium effect size, resonating with Rogers' (2003) characterisation of innovativeness as the defining trait of early adopters. Attitude towards livelihood diversification (r = 0.2793, p<0.01) was the second strongest correlate, consistent with the Theory of Planned Behaviour's proposition that favourable attitudes translate into behavioural intention. Risk orientation (r = 0.2362, p<0.01) was also significant, while material possession (r = 0.1700), economic motivation (r = 0.1759), and scientific orientation (r = 0.1744) showed smaller but consistent associations (all p<0.05). Contact with the project team (r = 0.1721, p<0.05), though significant, recorded one of the smallest effect sizes among the significant predictors a finding that qualifies rather than diminishes the role of extension contact: the volume of contact recorded (Mean = 7.00 visits) appears sufficient to reach significance, but the modest effect size suggests that the depth and participatory quality of interactions may matter more than their frequency, a pattern also noted by Sharma *et al*. (2024) and Warshini *et al*. (2022).

divergence is that FFP distributes technologies free of cost, which may weaken the leverage that income, landholding, and asset ownership typically exert in adoption decisions requiring upfront investment material possession being a partial exception, perhaps because it proxies not purchasing power but the general capacity to operate, maintain, and stay informed about new technologies once received, given that the index spans implements, transport, and communication assets. This remains an interpretation consistent with the data rather than a causally established mechanism, and would benefit from a comparative design contrasting FFP and non-FFP villages.

The non-significance of age, sex, education, landholding, annual income, and livestock possession diverges from adoption models that treat structural and demographic variables as primary determinants. The pattern most closely mirrors Rutsa and Jha (2023), who likewise found sex, education, landholding, and income non-significant for SRI adoption in Nagaland; it agrees partially with Sharma *et al.* (2024), who reported landholding, income, and farming experience as non-significant but, unlike the present study, found age and education significantly related to adoption; and it stands in clear contrast to Aziz *et al.* (2022), where nearly all structural variables were significant. One plausible, programme-specific explanation for this

### *Confidence Intervals for Significant Correlations*

**Table 5:** 95% Confidence Intervals for Significant Correlations (Fisher's Z-Transformation)

| Predictor Variable | r | 95% CI Lower | 95% CI Upper | Interpretation |
|---|---|---|---|---|
| Contact with Project Team | 0.1721 | 0.0051 | 0.3297 | Small, borderline — excludes zero |
| Material Possession | 0.1700 | 0.0029 | 0.3277 | Small, borderline — lower CI near zero |
| Innovativeness | 0.4213 | 0.2734 | 0.5497 | Medium, robust — wide CI above zero |
| Attitude–Livelihood Div. | 0.2793 | 0.1177 | 0.4265 | Small–medium, robust — CI clears zero |
| Economic Motivation | 0.1759 | 0.0091 | 0.3332 | Small, borderline — lower CI near zero |
| Scientific Orientation | 0.1744 | 0.0075 | 0.3318 | Small, borderline — lower CI near zero |
| Risk Orientation | 0.2362 | 0.0719 | 0.3880 | Small–medium, consistent — CI above zero |

The 95% confidence intervals provide a probabilistic complement to the significance tests. The interval for innovativeness (0.273–0.550) is the widest and most distant from zero, while material possession, contact with the project team, economic motivation, and scientific orientation all show lower bounds close to zero, indicating that although statistically significant, these four associations are modest and should be interpreted cautiously rather than treated as strong effects.

### *Partial Correlation Analysis - Controlling for Education*

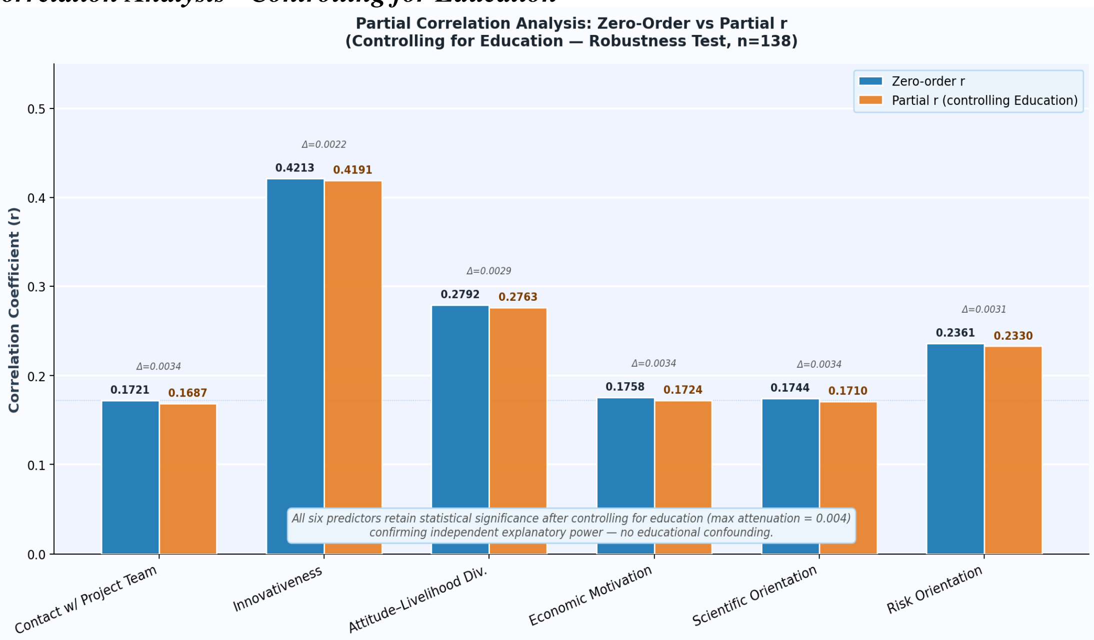


**Fig. 4 :** Zero-Order vs. Partial Correlations Controlling for Education

**Table 6:** Partial Correlation Analysis Controlling for Education (n = 137)

| Predictor Variable | Zero-order r | Partial r | t-partial | Significance |
|---|---|---|---|---|
| Innovativeness | 0.4214 | 0.4311 | 5.531 | ** (p<0.001) |
| Attitude–Livelihood Div. | 0.2788 | 0.2869 | 3.467 | ** (p<0.001) |
| Risk Orientation | 0.2295 | 0.2244 | 2.666 | ** (p=0.009) |
| Economic Motivation | 0.1569 | 0.1717 | 2.018 | * (p=0.046) |
| Scientific Orientation | 0.1802 | 0.1704 | 2.002 | * (p=0.047) |
| Material Possession | 0.1774 | 0.1582 | 1.854 | NS (p=0.066) |
| Contact with Project Team | 0.1688 | 0.1548 | 1.814 | NS (p=0.072) |

*Note: n = 137 (one respondent missing a Contact with Project Team value); zero-order r with adoption for education = 0.0844, NS.*

After controlling for the effect of education, innovativeness, attitude, risk orientation, economic motivation, and scientific orientation remained significantly associated with technology adoption. The partial correlation coefficients were very similar to the original correlation values, indicating that these relationships were independent of the beneficiaries' educational level. However, material possession and contact with the project team were no longer statistically significant after controlling for education ($p = 0.066$ and $p = 0.072$, respectively). This suggests that their initial association with technology adoption was partly influenced by the educational level of the beneficiaries rather than representing an independent relationship. These findings highlight that while behavioural characteristics continue to influence technology adoption regardless of education, the effects of material possession and project contact are, to some extent, linked with educational differences among the beneficiaries. This distinction, which could not be identified through simple correlation analysis alone, provided a clearer understanding of the factors influencing technology adoption and was considered in the subsequent regression analysis.

***Multiple Regression Analysis of Adoption Determinants***

The seven variables found significant at the bivariate stage (innovativeness, attitude towards livelihood diversification, risk orientation, economic motivation, scientific orientation, material possession, and contact with the project team) were entered simultaneously into an ordinary least squares regression predicting the adoption index (n = 137, one case excluded for a missing contact-with-project-team value).

**Table 7:** Multiple Regression Analysis — Predictors of Technology Adoption (n = 137)

| Predictor | B (unstd.) | SE(B) | Std. β | t | p | VIF |
|---|---|---|---|---|---|---|
| Constant | 6.253 | 8.571 | — | 0.730 | 0.467 | — |
| Innovativeness | 1.886 | 0.483 | 0.361 | 3.906 | <0.001** | 1.51 |
| Attitude–Livelihood Div. | 0.195 | 0.097 | 0.169 | 2.018 | 0.046* | 1.25 |
| Material Possession | 0.535 | 0.235 | 0.179 | 2.275 | 0.025* | 1.10 |
| Risk Orientation | 0.260 | 0.160 | 0.133 | 1.630 | 0.106 NS | 1.17 |
| Economic Motivation | 0.139 | 0.129 | 0.094 | 1.080 | 0.282 NS | 1.33 |
| Contact with Project Team | 0.359 | 0.334 | 0.088 | 1.075 | 0.284 NS | 1.18 |
| Scientific Orientation | -0.325 | 0.269 | -0.113 | -1.210 | 0.229 NS | 1.54 |
| Model Summary | $R^2 = 0.271$ | Adj. $R^2 = 0.231$ | $F(7,129) = 6.845$ | $p < 0.001$ | — | — |

*Note: * p<0.05; ** p<0.01; NS = not significant. Standardised β from mean-centred, unit-variance predictors. VIF = variance inflation factor. With heteroscedasticity-robust (HC3) standard errors, Innovativeness (p<0.001) and Material Possession (p=0.031) remain significant; Attitude becomes marginal (p=0.080); conclusions for the remaining predictors are unchanged.*

Before interpreting the regression results, the assumptions of the model were examined. The diagnostic tests showed no evidence of multicollinearity among the predictor variables, indicating that each variable contributed distinct information to the model. The residuals were normally distributed, and no influential observations or extreme outliers were detected. Although the Breusch–Pagan test indicated heteroscedasticity, robust standard errors were estimated, and the interpretation of the results remained unchanged.

The overall regression model was statistically significant ($F = 6.845$, $p < 0.001$) and explained 27.1% of the variation in technology adoption (Adjusted $R^2 = 0.231$). When all seven significant variables from the correlation analysis were entered into the model simultaneously, only innovativeness and material possession remained significant predictors of technology adoption. Although attitude towards livelihood diversification showed a weak positive effect, it was not consistently significant after applying robust standard errors. In contrast, risk orientation, economic motivation, contact with the project team, and scientific orientation, which were significant in the correlation analysis, did not retain their significance in the regression model. This indicates that their relationship with technology adoption was largely shared with other predictor variables rather than representing an independent contribution.

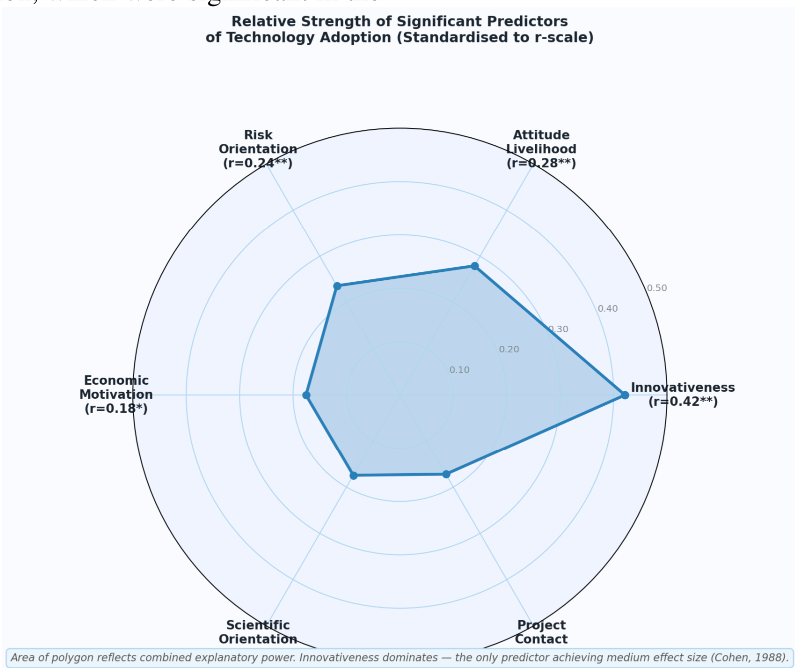


**Fig. 5:** Relative Strength of Significant Bivariate Predictors of Technology Adoption (Pearson r values; the joint regression above should be read alongside this bivariate summary, not in place of it)

Overall, the regression analysis provided a clearer understanding of the factors influencing technology adoption than the correlation analysis alone. While several variables were individually associated with adoption, innovativeness emerged as the most consistent and robust predictor across all analyses, followed by material possession. These findings, together with the partial correlation results, suggest that innovativeness plays the strongest independent role in explaining technology adoption among Farmer FIRST Programme beneficiaries. However, as the study is based on cross-sectional data, the observed relationships indicate statistical associations and should not be interpreted as evidence of causality.

## Conclusions, Limitations, and Policy Implications

This study set out to profile Farmer FIRST Programme beneficiaries in the mid-hill region of Uttarakhand, assess their extent of technology adoption, and identify which behavioural, attitudinal, institutional, and socio-economic variables are significantly associated with that adoption, both individually and jointly. Of the fourteen variables examined, seven were significantly correlated with adoption at the bivariate stage: innovativeness, attitude towards livelihood diversification, risk orientation, material possession, economic motivation, scientific orientation, and contact with the project team. Age, sex, education, landholding, annual income, and livestock possession showed no significant bivariate association, while occupation showed a small but significant association via one-way ANOVA. When all seven bivariate factors were combined into a multiple regression, only innovativeness and material ownership maintained independent explanatory weight (jointly with the other five predictors explaining 27.1% of adoption variation, Adjusted $R^2 = 0.231$). Material possession and communication with the project team were not statistically significant after education was controlled. Overall, our findings demonstrate that, across all levels of analysis, innovativeness is the most accurate and consistent predictor of adoption in this sample. Although the other institutional and behavioural elements are crucial on their own, they also greatly overlap with one another and, in some cases, with education.

The findings of this study should be interpreted in light of certain limitations. First, the study was confined to three villages under a single Farmer FIRST Programme implementation site, which may limit the generalisability of the findings to other agro-ecological regions or FFP centres. Future studies covering multiple programme locations would help validate the consistency of these results. Second, the cross-sectional nature of the study captures technology adoption at a single point in time and therefore cannot establish causal relationships between the variables. Third, the regression analysis showed unequal variability in prediction errors across respondents. However, the use of robust standard errors confirmed that the main findings remained unchanged. Future studies may apply alternative statistical models to further improve the analysis. Fourth, the number of agricultural labourers included in the study was relatively small; therefore, the findings related to occupation should be interpreted with caution.

Finally, the data were collected through a structured interview schedule administered to Farmer FIRST Programme beneficiaries. As the respondents were beneficiaries of a programme implemented by GBPUAT, some may have provided socially desirable responses while reporting their technology adoption behaviour, despite efforts to ensure objective data collection. Future studies may strengthen the validity of the findings by complementing farmers' responses with field observations or programme records. In addition, the regression model explained 27.1% of the variation in technology adoption, indicating that other factors not examined in the present study may also contribute to farmers' adoption behaviour. Recent adoption studies have highlighted the influence of technology-specific characteristics, market accessibility, institutional support, perceived usefulness, compatibility, social influence, self-efficacy, and facilitating conditions in shaping adoption decisions. Future research may therefore incorporate these emerging technological, behavioural, and contextual variables to develop a more comprehensive understanding of technology adoption under participatory extension programmes.

Despite these limitations, the findings have reasonable implications for extension practice. Identifying and engaging highly innovative farmers as peer-diffusion agents appears to be the single most defensible extension priority to emerge from this analysis, consistent with Rogers' (2003) diffusion framework and robust across every specification tested. Material possessions' independent contribution suggests that farmers with greater existing asset bases (implements, transport, communication devices) may be better positioned to operationalise newly adopted technologies, which could inform how FFP sequences complementary asset support alongside technology transfer. Given that attitude, risk orientation, economic motivation, scientific orientation, and extension contact were each significant on their own but did not survive jointly, extension programming built around any single one of these levers in isolation may be less effective than programming that treats innovativeness-building as the primary lever, with the others as secondary, mutually-reinforcing supports rather than independent channels. With female beneficiaries comprising 57.25% of the sample, extension materials and demonstration formats co-developed with women farmers and delivered in local languages remain a reasonable complementary recommendation. Future research employing longitudinal or comparative (FFP versus non-FFP) designs would substantially strengthen the causal interpretability of these policy directions.

***Declaration of Interest***

The authors declare no conflict of interest. The study was conducted as part of the first author's Master's dissertation at the Department of Agricultural Communication, College of Agriculture, GBPUA&T, Pantnagar, under the supervision of the co-authors.

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AUTHOR ACTION REQUIRED *"The author(s) used ChatGPT to edit and refine the wording of the result and Conclusion. All outputs were reviewed and verified by the author.*

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