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RESEARCH ARTICLE

Do nutri-cereal growers in Uttarakhand fit the same adopter profile - A cluster analysis of smallholder farmers

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Abstract

The diffusion of agricultural innovations often falters when dissemination strategies fail to account for the heterogeneity in adopter characteristics. A prevalent, yet flawed, assumption of farmer homogeneity frequently leads to the misattribution of adoption failures to the technology recipients rather than to the design of the diffusion process itself. This study challenges this assumption by segmenting smallholder nutri-cereal growers in Uttarakhand, India, into distinct adopter categories to inform more effective, targeted policy and extension strategies. Utilising the Hurt Innovativeness Scale, data from 247 farmers were subjected to latent class cluster analysis. The analysis delineated five distinct adopter categories: Innovators (7 %), Early Adopters (13.5 %), Early Majority (30.7 %), Late Majority (30.7 %) and Laggards (18 %). A notable finding is that the proportion of Innovators (7 %) substantially exceeds the 2.5 % benchmark established in Rogers' classical diffusion theory. This deviation suggests a nascent but significant shift towards a more innovation-receptive agricultural landscape in the region, likely propelled by the ongoing commercialisation of nutri-cereals. The study concludes that recognising and leveraging this heterogeneity is crucial for accelerating the adoption of sustainable agricultural practices. The identified clusters provide a robust framework for tailoring communication and intervention strategies, thereby enhancing the efficacy of innovation diffusion within smallholder farming communities.

Keywords: adopter categories; cluster analysis; growers; innovativeness; nutri-cereal; sustainability

Introduction

Indias' transition toward a green economy and Sustainable Development Goals (SDGs) relies heavily on its agricultural sector, particularly rain-fed agriculture, which covers 56 % of cultivated land and contributes 40 % of food production (1, 2). As food systems evolve from addressing hunger to promoting holistic nutrition and sustainability, millets have re-emerged as the vital crops for achieving food and livelihood security, particularly in marginal and rainfed regions (3). However, this sector receives limited research attention, especially on crops like millets, which are vital for rain-fed farming systems but have restricted market reach (4). Slow growth of coarse cereal and vulnerability to climate variability of staple crops hinder SDG targets like zero hunger and improved nutrition, disproportionately affecting rain-fed farmers whose livelihoods are intricately tied to rain-fed farming systems. Promoting innovations in nutri-cereal cultivation at a commercial scale could transform this sector, enhancing productivity, sustainability and climate resilience. Yet, adoption challenges persist because the social acceptance of such innovations depends on the structure and dynamics of the agricultural social system. Smallholder farmers, who are central to this transformation, are not a homogeneous group but vary widely in their needs, knowledge, experiences and preferences. Addressing their diversity is critical to fostering innovation adoption and driving sustainable agricultural growth (5, 6).

Recently, the year 2023 has been recognised as the International Year of Millets and has also highlighted the importance of these nutri-cereals, but achieving a significant increase in production requires sustained, targeted efforts. Transformative change must start with the producers, the first stakeholders in the value chain. In Uttarakhand, despite the introduction of innovations in nutri-cereal farming, adoption and diffusion remain limited. A key challenge lies in the blanket approach that fails to account for the diverse characteristics and needs of individual farmers. Understanding farmers' adoption categories is essential to designing tailored strategies that promote the effective integration of new technologies and practices (7, 8). Research indicates that the adoption of agricultural innovations depends on a range of farmer, farm and institutional and also upon individual innovational characteristics (9–14). Past studies exploring the importance of socioeconomic variables in innovation adoption decisions have yielded mixed results. Rogers categorised innovators as typically young, wealthy and educated, suggesting that age, income and education are critical determinants of innovation adoption. However, several studies have challenged these assertions. Research indicates that weak or non-existent correlations exist between socioeconomic factors like age, income and education and the adoption of innovations (15–17).

Research has examined the adoption of agricultural innovations in nutri-cereals, but very little attention has been given to classifying growers into adoption categories, particularly in Uttarakhand (18–21). To address this gap, the present study focuses on identifying and analysing adoption categories of nutri-cereal growers in Uttarakhand. This classification will guide policymakers, agricultural advisors, marketers and technology developers in crafting targeted strategies to enhance innovation adoption. By acknowledging the heterogeneity among farmers, this study aims to inform effective communication and support the promotion of nutri-cereal cultivation at a commercial scale in the district and Uttarakhand as a whole.

Concept of adopter categories

Not all potential adopters of an innovation adopt the new idea at the same time. Consequently, based on the degree of earliness to which an individual adopts the new product, adopters are classified into adopter categories. This division is necessary because it can assist in targeting, firstly, the prospects for a new product (i.e. potential innovators and laggards). Secondly, developing marketing strategies for penetrating various adopter categories and Third, predicting the continued acceptance of a new product. Development of adopter categories requires determination of the number of adopter categories, the percentage of adopters to include in each category and a method to define categories.

One assumes that the noncumulative adopter distribution takes the form of a bell-shaped curve. Consequently, using two basic statistical parameters of the normal adopter distribution-mean time of adoption (i) and its standard deviation (J)-one obtains five adopter categories mentioned in Fig. 1

Materials and methods

Sample and sampling procedure

The study was conducted in four districts of Uttarakhand (Almora, Pithoragarh, Pauri Garhwal and Tehri Garhwal, two each from the Kumaon and Garhwal regions). These districts were selected based on their highest nutri-cereal production, particularly small millets (Tehri Garhwal 19,527 tonnes; Almora 13552 tonnes (t); Pauri Garhwal 10630 t; Pithoragarh 1219 t) and finger millet (Almora 25440 t; Pauri Garhwal 13182 t; Tehri Garhwal 9,168 t; Pithoragarh 6778 t), as per the Department of Agriculture, Uttarakhand. Secondary data were collected from the respective block offices of each district. Four clusters, i.e. Duggada (Pauri Garhwal), Devprayag (Tehri Garhwal), Walthi (Pithoragarh) and Chaukhutiya (Almora) were purposively selected with support from Himmothan, a local NGO actively promoting millets in rainfed regions. These clusters represented patches with the highest nutri-cereal production and producers. Two villages per cluster were then selected based on the maximum number of households cultivating barnyard and finger millet for commercial purposes. In Garhwal, Kurn and Mahar (Devprayag) and Basyani and Mathana (Duggada) were selected, while in Kumaon, Rampur and Bagadi (Chaukhutiya) and Sirtola and Walthi (Walthi cluster) were included.

The total population comprised 642 individuals, from which a sample of 247 respondents was selected using probability proportionate sampling using Yamnae formula below. The data is collected through investigating farmers personally using an innovativeness scale. Yamnaes' formula for calculating the sample size, as given in equation 1:

$$n = N/(1+N(e)^2) \qquad \text{(Eqn. 1)}$$

Where n = sample size; N= Population size, e = taking 95 per cent confidence level with 5 per cent precision.

Data collection and tool

To categorise the farmers into the correct adopter categories, the study adopted the Hurt Innovativeness Scales (22). The Hurt, Joseph and Cook Innovativeness Scale is a 20-item self-report instrument designed to measure an individuals' global innovativeness, specifically their willingness to change and adopt new ideas. It is a short, valid and reliable Likert scale suitable for use in both self-administered questionnaires and face-to-face (personal) interviews. The scales measure individual degrees of innovativeness. It can be used before the innovation appears because it does not focus on the innovation; instead, the individual and how they behave. The scales have been used in many studies and have shown strong psychometric characteristics. It has repeatedly demonstrated its usefulness as a valid measure of general innovativeness (23). Items twenty were generated; these items were written based on the characteristics of the five adopter categories. The categories and a sample from each are as follows: innovator,' I consider myself adventuresome in a social system; early adopter, 'I consider myself as an opinion leader in a group I belong to; early majority, make decisions deliberately and methodically; late majority, I like stability and consistency; laggard, 'I am suspicious of new ideas. The questions were administered in a five-choice response format where respondents were instructed to give their level of agreement or disagreement with each of the twenty items on a scale of 1 (strongly disagree) to 5 (strongly agree). Scores were carefully assigned so that higher scores indicate a higher degree of innovativeness. To group smallholder farmers into the various adopter categories through latent cluster analysis and to check the assumption through ANOVA and performed in Jamovi software.

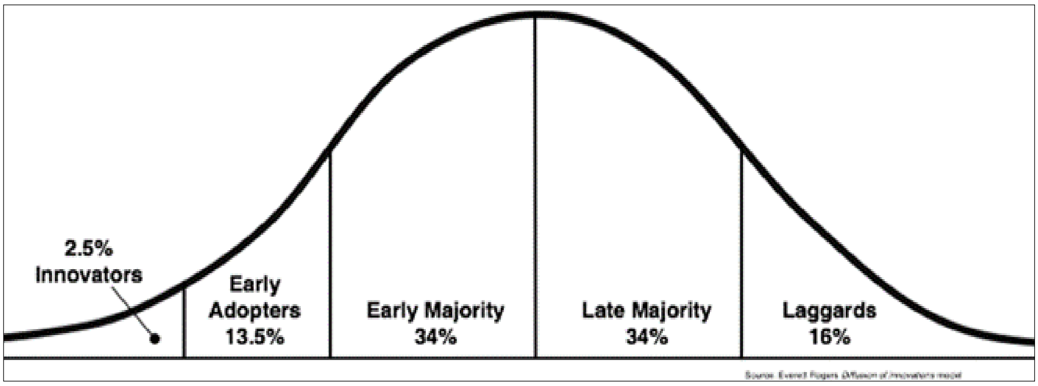

Fig. 1. Adopter categorisation.

Latent cluster analysis

The latent cluster analysis models are used to uncover unobserved heterogeneity in a population and to find substantively meaningful groups of people that are similar in their responses to measured variables (24). The LCA was selected over other classification techniques and factor analysis because it relaxes the assumptions of linearity, normal distribution and homogeneity of variance, lending itself to small data sets, such as the present study and those that cannot be analysed using conventional parametric clustering techniques (25). With 247 respondents, which is low for LCA, but some studies stated that if a high-quality indicator (innovativeness) is used with a strong theoretical background (i.e. adoptor categorisation), with clear class separation, with high entropy and clear model fit. The analysis was performed using Jamovi with the maximum likelihood method for parameter estimation. Under the present study, latent class cluster analysis was applied to classify the nutri-cereal growers into meaningful groups on the basis of their innovativeness. The Latent class cluster analysis was conducted under the steps mentioned in Fig. 2, given below.

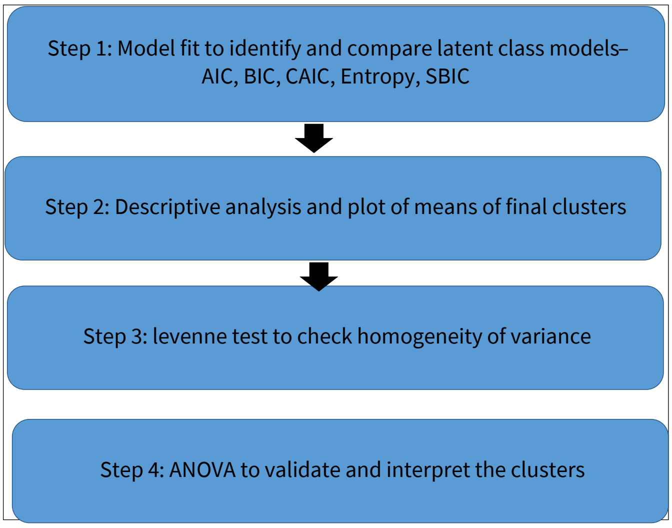

Fig. 2. Methodology of latent class cluster analysis.

Identifying and comparing the models-Models with one to seven classes were successively estimated. The optimal number of class memberships was determined by Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), likelihood-ratio statistic (G2) and entropy value (0.0–1.0) as the criterion (26). In LCA, these four criteria are used because together they help balance model fit, simplicity and accurate classification. Since LCA is a model-based clustering method, researchers need to decide on the number of latent classes that best represent the data without overfitting. The AIC, BIC and G2 decreased with an increase in the number of latent class models. However, the entropy values and identification of model fit showed that the four latent classes were the most suitable. Descriptive analysis–like Mean, plot and tests were performed to examine the distribution and prevalence of nutri-cereal growers based on the scale of innovativeness. Later, Levenes' test was conducted to measure homogeneity of variance (Levenes' test), and finally, based on the homogeneity result welch ANOVA for unequal variances was used when the groups differ greatly in their spread. ANOVA (Analysis of Variance) is often used in cluster analysis to evaluate the validity and meaningfulness of the clusters formed. Specifically, after clustering data, ANOVA helps assess whether the clusters are significantly different from each other based on certain variables. F-statistics measure how much variation exists between groups relative to within groups larger F value indicates bigger differences. The statistical significance level was set at $p<0.05$.

ANOVA (Analysis of variance) is often used in cluster analysis to evaluate the validity and meaningfulness of the clusters formed. Specifically, after clustering data, ANOVA helps assess whether the clusters are significantly different from each other based on certain variables. Heres' why it is conducted and what its values depict:

Results

Model fit

A total of six LCA models were fitted to the data. The comparative fit statistics of Latent Class Analysis (LCA) models presented in Table 1 provide insights into the models' fit and complexity across varying numbers of latent classes. The Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and Consistent AIC (CAIC) are indicators of model fit, where lower values suggest a better balance between goodness-of-fit and model parsimony. The results show a consistent decline in AIC, BIC and CAIC values as the number of latent classes increases, indicating an improvement in fit with more classes. The entropy, a measure of classification quality, remains high (close to 1) across all models, indicating clear and distinct classification of observations within each model.

The two-class model significantly improves fit over the one-class model, evidenced by a sharp drop in AIC, BIC and CAIC. As the number of classes increases further, the rate of improvement diminishes and the trade-off between fit and complexity becomes apparent. Notably, the six-class model has the lowest AIC fit statistics, suggesting it provides the best fit among the models considered. However, practical considerations, such as the interpretability and parsimony of the model, might make the five-class models preferable despite slightly higher fit statistics in comparison to the six. As demonstrated in Table 1, a five-class model differentiating between five different groups of adopters had an optimal fit to the data (BIC = 11049; AIC = 9536; CAIC =11353). Of course, the AIC index for this model was larger than that of the six-class model, but since it had a lower BIC and CAIC and entropy, there was compelling evidence for its optimal fit.

Table 1. Comparative fit statistics of the LCA model.

Model	AIC	BIC	CAIC	Entropy
One class model	14906	15185	15265	1.00
Two-class model	12211	12774	12935	1.00
Three-class model	11103	11950	12192	1.00
Four-class model	10259	11389	11712	1.00
Five-class model	9536	10949	11353	0.998
Six-class model	9353	11049	11534	1.00

The population share graph in Fig. 3 represents the results of a Latent Class Analysis (LCA), which identifies unobserved (latent) subgroups within a population based on responses to multiple observed variables. Each panel in the graph corresponds to one latent class and the bars represent the probability of endorsing each manifest variable (observed indicators) within that class. Here is a detailed breakdown. X-axis (manifest variables): Lists the observed variables used to distinguish the classes. Y-axis (probability): Represents the probability of a response for each manifest variable within a given class. Higher bars indicate a stronger association or endorsement of specific variables for that class. Fig. 3. depicts that

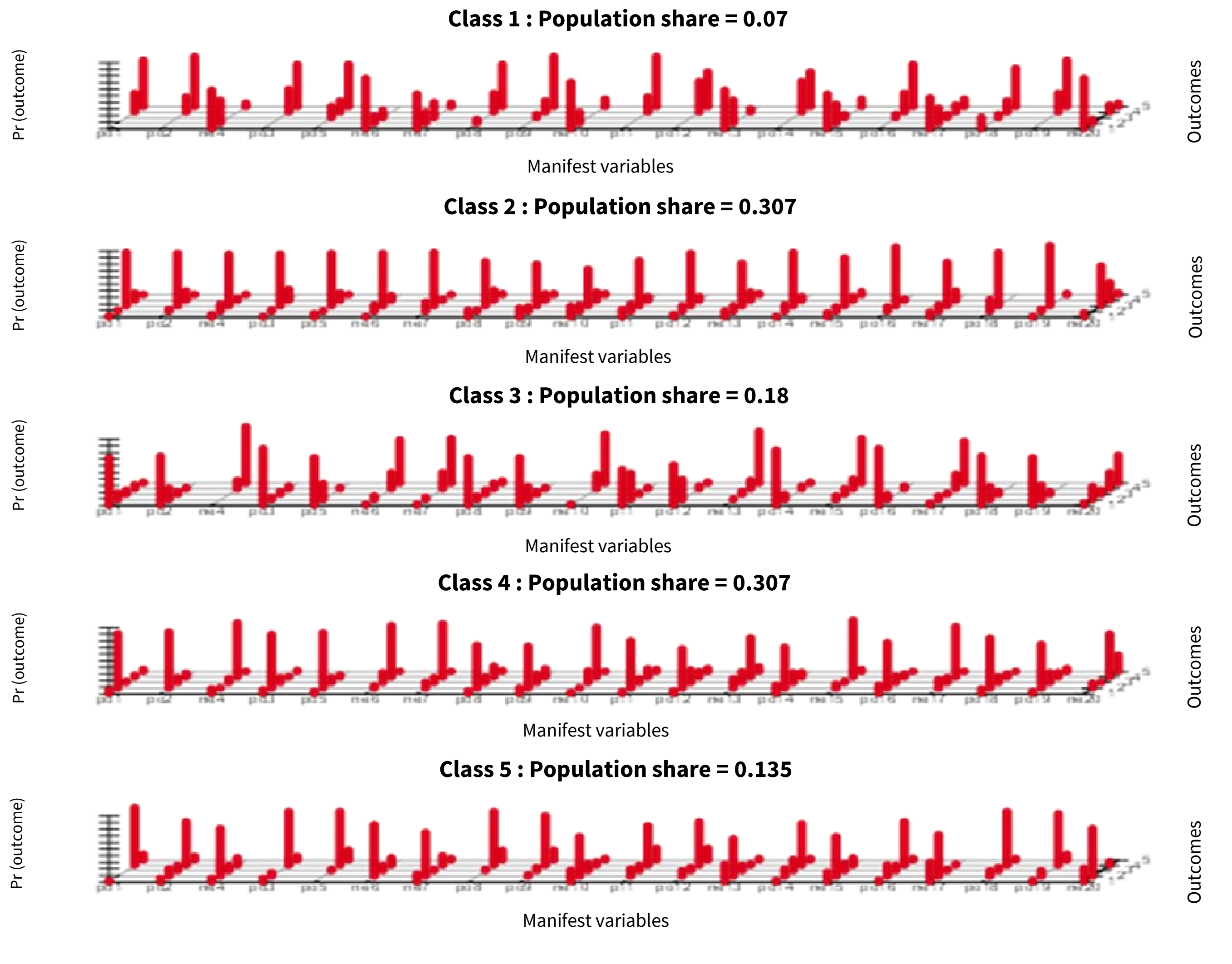

Fig. 3. Population share in cluster.

higher probability in a positive attribute (2, 3, 5, 7, 8, 9, 11, 12, 14, 16, 18 and 19) and lower probability in negative attributes items 4, 6, 7, 10, 13, 15, 17 and 20 in classes that were having higher innovativeness and vice versa result been observed in the classes with lower innovativeness.

Descriptive analysis

The bar chart illustrates Fig. 4 the responses to various items across five adopter categories: Innovators, Early Adopters, Early Majority, Late Majority and Laggards. Each category represents a stage in the adoption process. Innovators exhibit consistently high probability across most of the positive items, indicating their willingness to take risks and adopt innovations early. Early Adopters also show high scores but are more deliberate, often serving as influencers within their communities. The early majority displays moderate probability, reflecting their cautious approach to adoption, typically after observing initial success. The Late Majority, while similar to the Early Majority, has a slightly lower probability of adopting changes primarily due to societal or peer pressure. Laggards, on the other hand, have the lowest scores across most positive attributes items and high probability across most negative attributes, highlighting their reluctance or resistance to adopting changes, often due to traditional perspectives or resource limitations. The varying heights of the bars demonstrate differences in engagement and attitudes toward the items among these groups.

Cluster 1: Innovators (7 %)

This cluster comprises the smallest proportion of the population, i.e. total of eighteen individuals out of 247, which represents those who are highly receptive to new ideas, creative and willing to take risks. It is a highly proactive group that tends to strongly agree or agree with progressive or experimental ideas. The Table 2 of heat diagram, clearly represents high levels of agreement, with responses leaning heavily towards agree (23.5 %, 29.4 %, 35.7 %) and strongly agree (47.1 %,47.5 %, 65.4 %) of probability; with statements such as I1-My peers ask me for advice, I2: I enjoy trying new ideas, I4: I seek out new ways to do things,. However, their stance is less consistent on certain items, such as I3: I am generally cautious about accepting new ideas and I6: I am suspicious of new inventions and new ways of thinking. and I7: I rarely trust new ideas until I can see whether the vast majority of people around me accept them, where higher disagreement rates (35.3 %,76.5 %, 52.9 % for strongly disagree) suggest caution or selectivity about some initiatives. Their willingness to innovate is reflected in their high probability on items related to forward-thinking behaviours, such as I9: I consider myself to be creative and original in my thinking and behaviour (70.6 % strongly agree). The heat diagram represented in Table 2 clearly depicts, with green color that a higher probability is shown in strongly agree and agree for positive attribute whereas strongly disagree and disagree for negative attributes.

Cluster 2: Early majority (30.7 %)

This cluster comprises the maximum proportion of the population, i.e. total of seventy-six individuals out of 247 and represents individuals who are a substantial group that demonstrates a balanced approach toward innovation. They are receptive to new

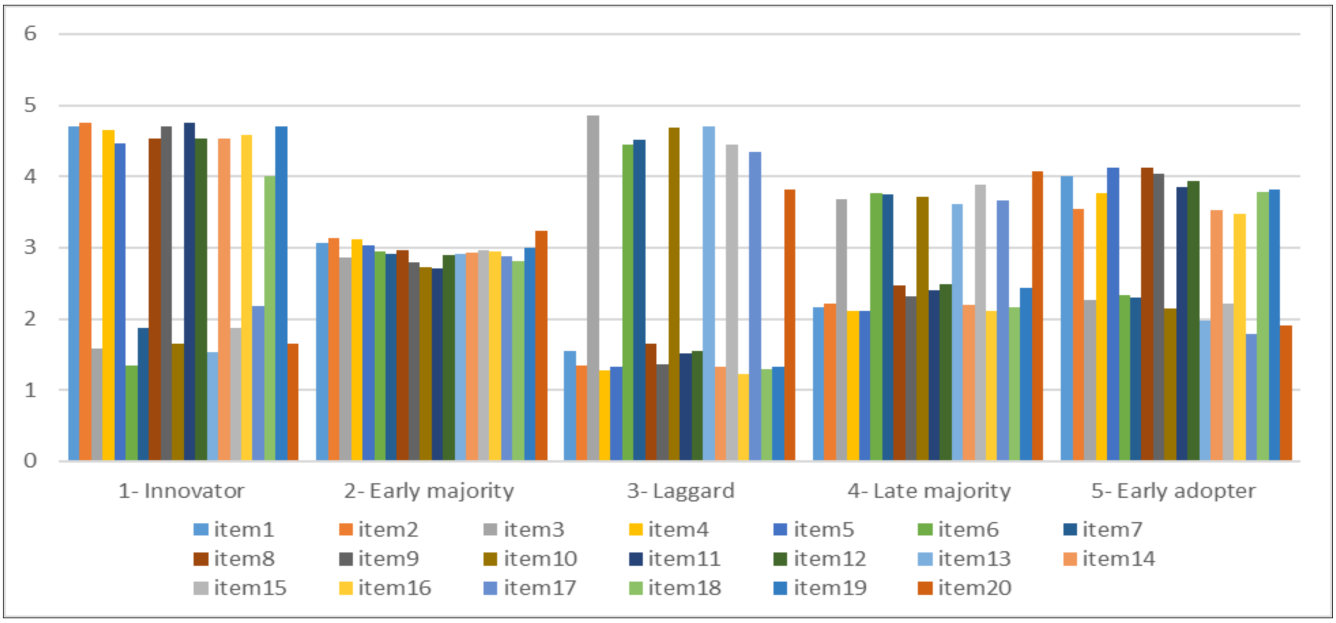

Fig. 4. Distribution of the variables' mean in each category.

Table 2. Item level Membership probabilities Heat map across the five different latent classes

	Cluster 1 – innovator (N=17)					Cluster 5 - Early adopter (N=33)					Cluster 2- Early majority (N=75)					Cluster 4- Late majority (N=75)					Cluster 3-laggard (N=44)				
	SD	D	N	A	SA	SD	D	N	A	SA	SD	D	N	A	SA	SD	D	N	A	SA	SD	D	N	A	SA
I1	5.9	11.8	11.8	23.5	47.1	6.1	6.1	3.0	81.8	3.0	2.7	2.7	81.3	12.0	1.3	6.7	82.7	2.7	4.0	4.0	72.7	11.4	6.8	6.8	2.3
I2	5.9	5.9	11.8	29.4	47.1	6.1	15.2	12.1	63.6	3.0	4.0	12.0	41.3	37.3	5.3	1.3	74.7	8.0	13.3	2.7	75.0	18.2	4.5	2.3	0.0
I3.	35.3	29.4	17.6	5.9	11.8	6.1	66.7	9.1	12.1	6.1	4.0	10.7	64.0	20.0	1.3	8.0	1.3	6.7	82.7	1.3	0.0	2.3	6.8	15.9	75.0
I 4	0.0	0.0	0.0	35.3	64.7	6.1	6.1	3.0	81.8	3.0	1.3	2.7	78.7	17.3	0.0	6.7	81.3	8.0	1.3	2.7	86.4	4.5	4.5	4.5	0.0
I5	0.0	0.0	17.6	29.4	52.9	3.0	3.0	6.1	78.8	9.1	5.3	10.7	62.7	18.7	2.7	4.0	84.0	8.0	4.0	0.0	61.4	25.0	11.4	2.3	0.0
I6	76.5	11.8	11.8	0.0	0.0	3.0	72.7	9.1	9.1	6.1	1.3	12.0	48.0	32.0	6.7	0.0	4.0	16.0	78.7	1.3	2.3	6.8	0.0	25.0	65.9
I7	52.9	17.6	23.5	0.0	5.9	12.1	66.7	3.0	15.2	3.0	5.3	14.7	65.3	10.7	4.0	0.0	9.3	8.0	81.3	1.3	2.3	4.5	0.0	25.0	68.2
I 8	0.0	5.9	0.0	35.3	58.8	6.1	0.0	3.0	75.8	15.2	10.7	2.7	68.0	16.0	2.7	5.3	65.3	9.3	17.3	2.7	72.7	6.8	6.8	9.1	4.5
I 9	0.0	0.0	5.9	23.5	70.6	3.0	3.0	6.1	72.7	15.2	14.7	8.0	64.0	10.7	2.7	9.3	64.0	13.3	13.3	0.0	72.7	20.5	4.5	2.3	0.0
I 10	58.8	17.6	11.8	0.0	11.8	18.2	60.6	12.1	6.1	3.0	17.3	12.0	49.3	18.7	2.7	2.7	1.3	18.7	76.0	1.3	2.3	0.0	0.0	22.7	75.0
I 11	0.0	0.0	0.0	23.5	76.5	3.0	12.1	9.1	57.6	18.2	13.3	12.0	57.3	16.0	1.3	4.0	72.0	6.7	13.3	4.0	54.5	40.9	2.3	2.3	0.0
I 12	0.0	0.0	0.0	52.9	47.1	3.0	9.1	6.1	63.6	18.2	8.0	9.3	64.0	12.0	6.7	5.3	60.0	20.0	9.3	5.3	61.4	31.8	0.0	4.5	2.3
I13.	52.9	35.3	5.9	5.9	0.0	27.3	57.6	9.1	3.0	3.0	9.3	12.0	53.3	21.3	4.0	0.0	14.7	17.3	60.0	8.0	0.0	2.3	4.5	13.6	79.5
I 14	0.0	0.0	0.0	47.1	52.9	3.0	12.1	18.2	63.6	3.0	4.0	13.3	60.0	16.0	6.7	13.3	62.7	16.0	8.0	0.0	84.1	9.1	0.0	4.5	2.3
I 15	52.9	29.4	11.8	5.9	0.0	15.2	60.6	12.1	12.1	0.0	6.7	22.7	52.0	13.3	5.3	4.0	13.3	16.0	62.7	4.0	0.0	6.8	9.1	15.9	68.2
I 16	0.0	5.9	5.9	35.3	52.9	3.0	18.2	9.1	66.7	3.0	2.7	10.7	81.3	4.0	1.3	13.3	69.3	10.7	5.3	1.3	86.4	9.1	0.0	4.5	0.0
I 17	47.1	23.5	5.9	11.8	11.8	30.3	63.6	3.0	3.0	0.0	8.0	10.7	38.7	38.7	4.0	0.0	13.3	8.0	77.3	1.3	4.5	6.8	2.3	22.7	63.6
I18	17.6	5.9	5.9	17.6	52.9	3.0	9.1	6.1	78.8	3.0	4.0	14.7	40.0	38.7	2.7	8.0	76.0	9.3	5.3	1.3	75.0	20.5	4.5	0.0	0.0
I 19	5.9	5.9	5.9	23.5	58.8	6.1	9.1	3.0	75.8	6.1	5.3	12.0	72.0	8.0	2.7	4.0	66.7	16.0	8.0	5.3	72.7	22.7	4.5	0.0	0.0
I 20	58.8	11.8	11.8	11.8	5.9	21.2	63.6	3.0	6.1	6.1	6.7	10.7	50.7	28.0	4.0	6.7	13.3	10.7	46.7	22.7	2.3	4.5	4.5	34.1	54.5

ideas but prefer to see evidence of their success before adoption. This group (37.8 %) moderately agree with statements like I2: I enjoy trying new ideas and 38.7 % moderately agree with I18: I am receptive to new ideas, while 38.7 % agree with cautiously endorsing I17: I must see other people using innovations before I will consider them. However, neutrality is more prevalent in this group than in Innovators or Early Adopters, indicating their cautious and evaluative nature. The heat diagram represented in Table 2 clearly reveals that a higher probability is shown in neutral and agree for positive attribute whereas neutral and disagree for negative attributes.

Cluster 3: Laggards (18 %)

This cluster comprises the maximum proportion of the population, i.e. total of forty-four individuals out of 247 and represents individuals who exhibit the highest level of scepticism and are the least likely to adopt innovations. Table 2 depicts that 68.2 %, 54.5 % strongly agree with statements like I7: I rarely trust new ideas until I can see whether the vast majority of people around me accept them and I15: I tend to feel that the old way of living and doing things is the best, respectively. The heat diagram clearly depicts a higher probability being shown in strong disagreement for positive attribute whereas strong agreement for negative attributes.

Cluster 4: Late majority (30.7 %)

This class comprise of maximum composition proportion of the population, i.e. total of seventy-five individuals out of 247. This cluster shares some similarities with the Laggards in their cautious approach, but is less resistant to change. They adopt innovations reluctantly and under pressure, such as peer influence or necessity. This is reflected in their response higher level of agreement of items showing sceptical behaviour like I6 and I7 (I6- I am suspicious of new inventions and new ways of thinking., I7- I rarely trust new ideas until I can see whether the vast majority of people around me accept them.) Also, probability about 60 % and 77.3 % of the respondents agree with statements such as I13: I am reluctant about adopting new ways of doing things until I see them working for people around me and I17: I must see other people using innovations before I will consider them, respectively. While they are slower to adopt compared to the Early Majority, Late Adopters are more willing to accept change once it has been proven effective. Their behaviour reflects a careful balance between scepticism and gradual acceptance.

Cluster 5 : Early adopters (13.5 %)

This smaller segment of the Early Majority overlaps in characteristics with Cluster 2 but demonstrates a slightly higher inclination toward leadership and influence. This cluster plays a pivotal role in bridging the gap between Innovators and the larger majority. They show strong agreement on several key items, particularly I2, I enjoy trying new ideas and I4- I seek out new ways to do things, where over 63 % agree or strongly agree. Unlike Innovators, Early Adopters exhibit a slightly more cautious approach, with responses across I6 and I7 reflecting higher levels of neutrality or disagreement, 45.5 %, 48.5 % Disagree; 30.1 % 21.2 % Neutral for I6- I am suspicious of new inventions and new ways of thinking. I7- I rarely trust new ideas until I can see whether the vast majority of people around me accept them. They moderately agree with statements such as I8: I feel that I am an influential member of my peer group and I5: I frequently improvise methods for solving a problem when an answer is not apparent. This group is deliberate in their adoption decisions but shows more willingness to engage in leadership roles, making them an essential influencer within their peer networks during the innovation adoption process. This class suggests they are strategic and practical, looking for proven benefits before adopting new practices. Their significant agreement rates on most items highlight their openness to change and their critical role in influencing the broader adoption of new ideas.

Homogeneity of clusters and One-way ANOVA

Homogeneity of variance is a crucial assumption in many parametric tests, such as ANOVA, which assumes that the variances of the dependent variable are equal across the groups being compared. To assess the homogeneity among the different groups levenne test was conducted and revealed in Table 3, as in some items, the assumption is violated *($p < 0.05$)*, alternative methods like Welchs' ANOVA tests may be more appropriate. Table 3 states that a higher F -value of Item 1, 2, 3, 4, 5, 9, 11, 16, 17, 18 and 19 suggests that the means of the clusters are more widely separated relative to the variability within clusters, implying greater distinctiveness. p value less than 0.05 clearly defines that the differences in means across clusters are statistically significant.

Discussions

The adoption framework for nutri-cereal growers in Uttarakhand reveals that a five-class model is the best fit, indicating that growers are not homogeneous and can be segmented into specific adopter categories. Notably, the proportion of innovators (Cluster 1) in this context is 7 %, which is significantly higher than Rogers' theoretical benchmark of 2.5 %. Research has demonstrated similar results (27). This elevated percentage reflects the specific dynamics of moving nutri-cereals from subsistence to commercial cultivation. This transition is encouraged by an environment that provides policy support, market incentives and assured market outlets, alongside the promotion of these crops as climate-resilient. This context lessens the perceived risk, allowing farmers to exhibit creativity and enthusiasm for exploration, positioning them as crucial drivers of early adoption, even while maintaining a somewhat cautious and selective approach to unfamiliar ideas. The higher share of innovators in Uttarakhand is rooted in this encouraging environment, combined with long-standing indigenous knowledge that inherently reduces the perceived risk of adopting new practices. Furthermore, the innovators demonstrate curiosity and openness to ambiguity, adopting new ideas quickly with minimal reliance on external validation. Innovativeness in this sector is fundamentally shaped by cultural, institutional and market factors. Culturally, traditional recipes and local knowledge drive authentic product creation (like Mandua cookies, Jhangora kheer) and help mitigate risk. Institutionally, support from bodies like ICAR-IIMRs' Nutrihub, government schemes and extension services provides essential R and D, funding and market linkages crucial for innovation and commercial success. Lastly, market factors, including the demand for health foods, the use of digital platforms for branding and linkages with corporate partners, transform local produce into viable commercial products, driving the shift from subsistence to commercial success and fostering opportunities for new entrepreneurs.

The combined size of the Early Majority (Cluster 2) and the Late Majority (Cluster 4), which collectively accounts for a substantial 61.4 % of the growers, highlights the critical phase the nutri-cereal sector in Uttarakhand has reached (28). These two groups together constitute the tipping point for diffusion, making their engagement

Table 3. To check the homogeneity of variance and One-way ANOVA.

	Homogeneity of variances Test (Levenes' test)					One-way ANOVA (Welchs')			
	F	df1	df2	P value	Result	F	df1	df2	p
1	7.26	4	239	0.001	Significance	116.7	4	78.3	***
2	8.21	4	239	0.001	Significance	166.7	4	74.7	***
3	4.33	4	239	0.002	Significance	196.3	4	73.0	***
4	1.71	4	239	0.147	Not Significance	137.6	4	74.6	***
5	3.98	4	239	0.004	Significance	197.9	4	74.7	***
6	7.90	4	239	0.001	Significance	84.7	4	71.1	***
7	9.54	4	239	0.001	Significance	55.1	4	68.4	**
8	8.36	4	239	0.001	Significance	77.2	4	78.6	***
9	3.16	4	239	0.015	Significance	132.7	4	80.9	***
10	4.01	4	239	0.064	Not Significance	68.7	4	71.8	*
11	1.89	4	239	0.112	Not Significance	137.6	4	83.9	***
12	7.23	4	239	0.01	Significance	82.0	4	77.2	***
13	1.32	4	239	0.263	Not Significance	92.1	4	75.8	***
14	5.99	4	239	0.001	Significance	95.2	4	74.0	***
15	6.80	4	239	0.001	Significance	52.2	4	70.0	***
16	11.00	4	239	0.001	Significance	114.8	4	68.5	**
17	7.51	4	239	0.001	Significance	160.2	4	72.0	***
18	11.89	4	239	0.002	Significance	101.6	4	69.4	***
19	13.12	4	239	0.001	Significance	160.4	4	75.5	***
20	10.67	4	239	0.001	Significance	60.8	4	72.6	**

(Significance ******* 0.001,******0.01, *****0.05).

essential for transitioning the commercial level of nutri-cereal cultivation from early experimentation to widespread mainstream adoption. Adopter categories serve as an effective framework for segmenting these target audiences to design and implement focused interventions.

While both groups are crucial for scale-up, they possess distinct needs and adoption drivers. The Early Majority farmers are generally deliberate and strongly guided by practicality. Although they are socially connected, they adopt innovations only after observing successful outcomes among peers, thereby playing a crucial role in bridging early adopters with the wider farming community. In contrast, the Late Majority are more risk-averse, possess weaker external linkages and rely heavily on local norms, collective decisions and visible economic benefits before adoption.

Given these differences, diffusion strategies must be multifaceted. For both groups, strategies should emphasise peer-led demonstrations, farmer-to-farmer testimonials and evidence of economic returns. To accelerate adoption, interventions must strengthen social proof through progressive farmers. Furthermore, because risk aversion is a key barrier, particularly for the Late Majority, interventions must ensure assured markets and provide risk-reduction mechanisms such as input support, price incentives and extension follow-up. Ultimately, activating this large majority requires targeted diffusion strategies that combine social learning, economic assurance and institutional support to accelerate the scaling of nutri-cereals within smallholder farming systems. This institutional support should leverage existing factors such as government schemes, extension services and market linkages that are already fostering innovation and commercialisation.

Cluster five occupies a central position in the social network, with members frequently approached by others for advice and guidance, making them well-suited for leadership roles. Although they are not the earliest adopters, they play a critical role in accelerating diffusion by bringing innovations closer to their peer groups due to their accessibility and trustworthiness. In terms of external linkages, these well-connected farmers receive information and technologies through contacts outside the village and from extension personnel. While innovators and early adopters actively gather information from mass media and are willing to adopt with minimal encouragement, these findings highlight that adopter classes differ in their internal and external network structures. This group needed to be empowered as a local opinion leader through targeted training and timely technical support. Lastly, cluster 3 – laggards is characterised by a strong preference for tradition, risk aversion and a reluctance to embrace change. Their cautious nature makes them the last group to adopt innovations, often requiring widespread social proof and external pressures. It is very difficult to upgrade laggards, making behavioural change particularly challenging for laggards. To bring change in laggards, interventions should focus on community-based approaches, using trusted local leaders and collective decisions rather than individual targeting. Also, the ANOVA results imply that the clusters are internally homogeneous (similar within clusters) but externally heterogeneous (different across clusters), which is the desired outcome of clustering.

Conclusion

The study provides comprehensive evidence regarding the different innovation adopter categories among nutri cereal growers of the Uttarakhand region, offering a valuable understanding of the dynamics shaping this sector. The findings of the study reveal that the early majority and the late majority alone combine to make around 61 per cent. This implies that those in the early majority and the late majority categories are the main determiners of innovation adoption. The present study showed an upward increase in innovativeness to an upwards increase in less innovativeness. For instance, innovators are 7 % in the current study as against 2.5 % in Rogers and Laggards are 18 % presently as against 16 % in Rogers, whereas both early and late majority percentage was decreased from 34 to 30.7 %. Therefore, the obtained result suggests that a result from a macro-level study (used by Rogers) may not show the same result at the micro-level (present study). i.e., Rogers' work was developed for the market at a large scale, whereas the current study was developed for a category of growers, i.e. micro-scale. Also, the area selected within the study was mainly the areas where nutri-cereals were grown in the maximum amount. These trends suggest that the region holds immense potential for fostering more Innovators and Early Adopters in the future and indicate a growing interest in nutri-cereals, fueled by their increasing commercialisation and the gradual development of their value chain. This shift could accelerate the adoption of advanced practices and technologies, further enhancing the profitability and sustainability of nutri-cereal cultivation in Uttarakhand, ultimately contributing to its role as a model for agricultural innovation and value chain development. Further research should delve deeper into the socio-economic characteristics of farmers, which can be integrated alongside the innovativeness scale to enhance the identification and understanding of clusters and will offer a more holistic approach that will refine the cluster analysis.

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Authors' contributions

SB carried out conceived and designed the study framework, collected data, literature review analysed the data, drafted the manuscript, data collection and literature review. MAA assisted in the interpretation and revision of the manuscript. Both authors read and approved the final version of the manuscript. All authors read and approved the final manuscript

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