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RESEARCH ARTICLE

Risk aversion model for small and marginal farmers in the Cauvery Delta Zone, Tamil Nadu

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Abstract

Agriculture in India largely depends on the monsoon. As a result, the production of food grains fluctuates year after year. Although the ownership of agricultural land in India is fairly widely distributed, there is some degree of concentration of landholding. A farmer is often required to make decisions under various vulnerable and uncertain conditions, which stem from social uncertainties, natural hazards, market fluctuations and changes in state policies. Risk aversion is the tendency to avoid risk and have a low risk tolerance. The districts of Thanjavur, Tiruvarur and Nagapattinam in the Cauvery Delta Zone were selected for the study due to their risk-prone areas and crops affected by natural calamities. The total sample size for the study was 366 and it was estimated by the Cochran's sample size formula and the samples were selected by using a proportionate random sampling technique. The standardized coefficient of demise of an elder in the family (P1) was 0.797, dissension among family members (P2) was 0.829, parental control on decision making (P3) was 0.681 and location of farmlands in risk-prone areas (P4) was 0.604 and represents the partial effect of the personal factor. The hurdles in the procurement process (M1) were 0.519, lack of infrastructure facilities in the markets (M2) was 0.774, increase in transportation charges (M3) was 0.685 and timely unavailability of procurement centres (M4) was 0.542 and together represented the partial effect of the market factor. These factors not only increase the transaction costs for farmers but also reduce their bargaining power, delay the sale of produce and in some cases compel distress sales. Although risk management strategies are adopted more frequently by farmers with higher risk aversion, the overall differences across groups are relatively small. This suggests that many farmers, regardless of their individual risk tolerance, remain exposed to similar structural challenges. Beyond individual coping strategies, systemic reforms are needed. Strengthening rural infrastructure, improving procurement processes and ensuring timely market access can reduce risks, stabilize incomes and enhance resilience for farmers in risk-prone areas.

Keywords: aversion; Cauvery delta zone; factor; farmers; risk behaviour

Introduction

Risk and uncertainty are more prominent in the agricultural sector than in the industrial sector, as farming is exposed to multiple types of risks from the field to the market. Farmers are often compelled to make critical decisions under vulnerable and uncertain situations, which arise from social uncertainties, natural hazards, market fluctuations and state policies. In this context, a key research question emerges: How can strategic models of risk aversion be developed to strengthen the decision-making capacity of small and marginal farmers in the Cauvery delta zone? This forms the central objective of the present study. Agricultural risks in developing countries mainly arises due to variations in geographical regions, risk-prone areas, climate change effects, seasonality in farm production, pest and disease infestations, fluctuating market demand for agricultural commodities, input and output price volatility and inadequate financial support in terms of credit and insurance. These risks directly affect agricultural production, which in turn influences farmers' income and livelihoods (1).

India, with a population of 1424 million, faces the pressing challenge of maintaining food security (2). If farmers are risk averse, resources may be misallocated, reducing overall production and affecting food availability. Conversely, if they are risk neutral, their production choices may alter expected marginal productivity (1).

Rice farming in the rainfed regions, particularly in Tamil Nadu's Cauvery delta, faces heightened risks due to uncertain climatic conditions, degraded soil, water deficits and underdeveloped markets. Rice is water-intensive and any shortage has severe impacts on yield (3). Tamil Nadu produced 7.265 million tonnes of rice from 2.04 million hectares in 2019-2020, with about 73 % of the Cauvery delta's 4.8 million people engaged in farming, fishing and livelihoods dependent on water resources. Small and marginal farmers, who often rely on informal loans from moneylenders and landlords, are particularly vulnerable. Their small landholdings are insufficient for collateral (4). Indebtedness has been a major factor linked to farmer suicides in the delta (5).

Earlier studies highlight that farmers' perceptions of risk vary: experienced and educated farmers emphasize market risks, while less experienced and less-educated farmers focus more on biological risks (6). Farming outcomes also depend on heterogeneity across systems, geophysical conditions and the farmer's managerial acumen (7). With this background, the study is specifically focused on developing a strategic risk aversion model for small and marginal farmers in the Cauvery delta zone.

Materials and Methods

Tamil Nadu was classified into seven agro-climatic zones based on soil characteristics, rainfall distribution, irrigation pattern, cropping pattern, other ecological and social characteristics. It comprised of North eastern zone, North western zone, Western zone, Cauvery delta zone, Southern zone, High rainfall zone and Hilly area & Tribal zone. From these zones, the Cauvery delta zone was selected purposively for the study on the basis of social characteristics, risk prone areas and crops affected by natural calamities. This zone had a total geographical land area of 1.45 million ha, i.e., was equivalent to 11 % of the area of Tamil Nadu state. The principal crop in this zone was rice and it was cultivated either single-cropped or as a double-cropped per year. The landholdings in the delta were quite small, with more than 60 % of farmers owning less than two hectares. Population growth had progressively diminished the size of landholdings. Fig. 1 depicts the study area, the districts of Thanjavur, Tiruvarur and Nagappattinam in the Cauvery Delta Zone were selected for the study due to risk-prone areas and crops being affected by natural calamities. The total sample size for the study was 366 and it was estimated by Cochran's sample size formula; the samples were selected by using a proportionate random sampling technique and presented in Table 1.

Cochran formula is:

$$n_0 = \frac{Z^2pq}{e^2}$$

Where

e is the desired level of precision (i.e. the margin of error) 5 %

p is the (estimated) proportion of the population which has the attribute in question (p = 0.6, i.e., Three-fifth of the landholdings are owned by marginal and small farmers)

q is 1 - p (q = 0.4)

The z-value is found in a Z table (for 95 % Confidence Interval i.e., z =1.96)

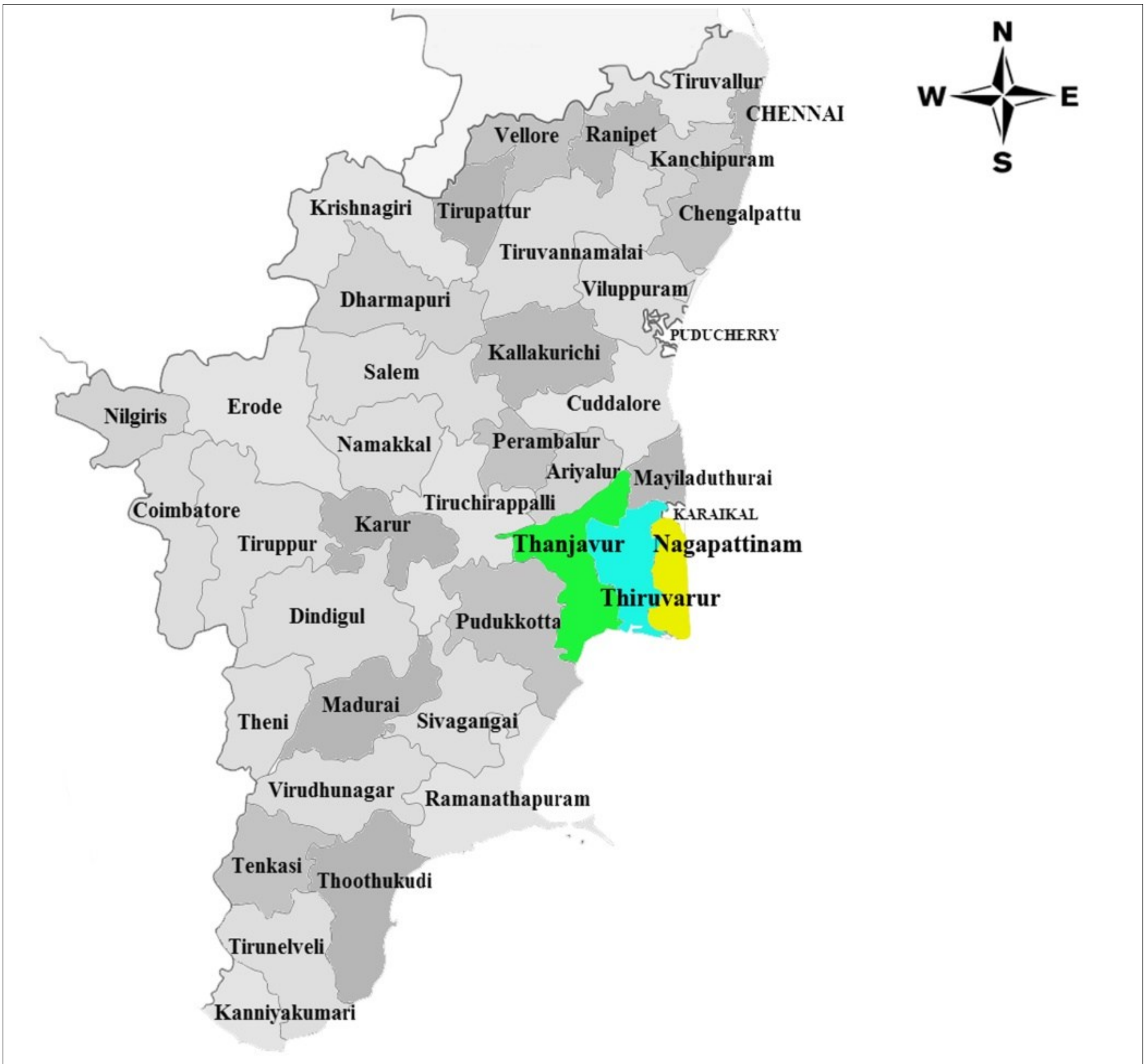

Fig. 1. Map showing the study area.

Table 1. Sample distribution from the selected villages

S. No.	Districts	Blocks	Selected villages	Marginal /Small farmer in selected villages	No. of farmers selected		Total
					MF	SF	
1.	**Thanjavur**	Ammapettai	Melatur	558	14	14	**122**
			Raramuthiraikottai	532	13	13	
		Orathanadu	Nadur	575	17	17	
			Thennamanadu	573	17	17	
2.	**Thiruvarur**	Needamangalam	Adhanur	312	16	16	**122**
			Royapuram	322	17	17	
		Mannargudi	Moovanallur	248	13	13	
			Painganadu	306	15	15	
3.	**Nagapattinam**	Kilvelur	Vadakarai	350	16	16	**122**
			Okkur	342	15	15	
		Thirumarugal	Thirukannapuram	340	15	15	
			Iravancehry	332	15	15	
Total		**6 Blocks**	**12 Villages**		**183**	**183**	**366**

$$\text{Sample size} = \frac{1.96^2(0.6)(0.4)}{0.05^2} = 368.79 \sim 366$$

(equal allocation of sample for 3 districts without oversampling)

An equal number of marginal and small farmers were selected and the categorization of land possessed was less than one hectare for marginal farmers and one to two hectares for small farmers as the classification mentioned in was followed in this study (8).

The statements were collected from the past literature and discussions with experts. The statements were measured on a five-point continuum viz., Strongly agree, Agree, Neutral, Disagree and Strongly Disagree, with scores of 5,4,3,2 and 1, respectively. The scoring procedure was developed as per a previous study. Initially, pilot testing was conducting for the statements with 100 farmers in the Cauvery Delta Zone and the responses were grouped by Exploratory factor analysis. The KMO value was 0.5 confirmed the sample adequacy and the factor loadings above 0.3 were considered and grouped into seven factors, viz., Personal, Family, Financial, Technological, Psychological, Social and Market factors.

Risk aversion factor

The data were collected from 100 farmers in Thanjavur, Thiruvarur and Nagapattinam districts and were analyzed using Exploratory Factor Analysis (EFA) to identify the latent factor structure. The sample size of 100 farmers was chosen to balance both statistical requirements and practical feasibility. The Kaiser -Meyer-Olkin (KMO) value of 0.5 and a significant Bartlett's Chi-square (χ^2 = 3211.19, $p < 0.000$) confirmed the adequacy of the sample size. Seven factors with eigenvalues greater than one were retained, together explaining 69.83 % of the total variance well above the acceptable 60 % threshold. The pattern matrix showed that all items loaded cleanly (≥ 0.3) on their intended factors.

1. Personal (11.90 % variance)

Reflected individual attributes such as age, education, health and decision-making style.

2. Psychological (7.15 % variance)

Related to attitudes, perceptions of risk, stress levels and confidence in managing uncertainties.

3. Financial (11.57 % variance)

Covered access to credit, savings, investment capacity and exposure to debt.

4. Social (6.90 % variance)

Captured community networks, peer influence and participation in farmer groups or cooperatives.

5. Family (8.49 % variance)

Represented household dynamics, including family support, conflicts and generational roles in farming decisions.

6. Market (5.01 % variance)

Focused on procurement facilities, infrastructure, pricing and market access (two weak-loading items were eliminated from this factor).

7. Technological (18.77 % variance)

Captured farmers' use of modern tools, inputs and practices to enhance productivity.

By distinguishing personal (individual characteristics), family (household-level influences) and psychological (mindset and attitudes), the analysis avoided redundancy while ensuring that each factor reflected a distinct dimension of farmers' risk environment.

Results

Strategic risk aversion model for small and marginal farmers

Measurement model for risk aversion

The measurement model on risk aversion, presented in Fig. 2, examined the relationship between the latent variables and their measures.

The results presented in Table 2 demonstrated that the specified model achieved a good fit based on various measures (10-12). The Normed Chi-square value was 1.664, while the absolute fit measures included GFI = 0.904, AGFI = 0.880, RMR = 0.050 and RMSEA = 0.043. Incremental fit measures such as NFI = 0.856, IFI = 0.937, TLI = 0.926 and CFI = 0.936 indicate an acceptable model fit. Parsimonious fit measures, including PGFI = 0.728, PNFI = 0.741 and PCFI = 0.810, further supported the model's reliability. Additionally, Cronbach's alpha value was 0.804. which indicated high internal consistency and reliability of the model.

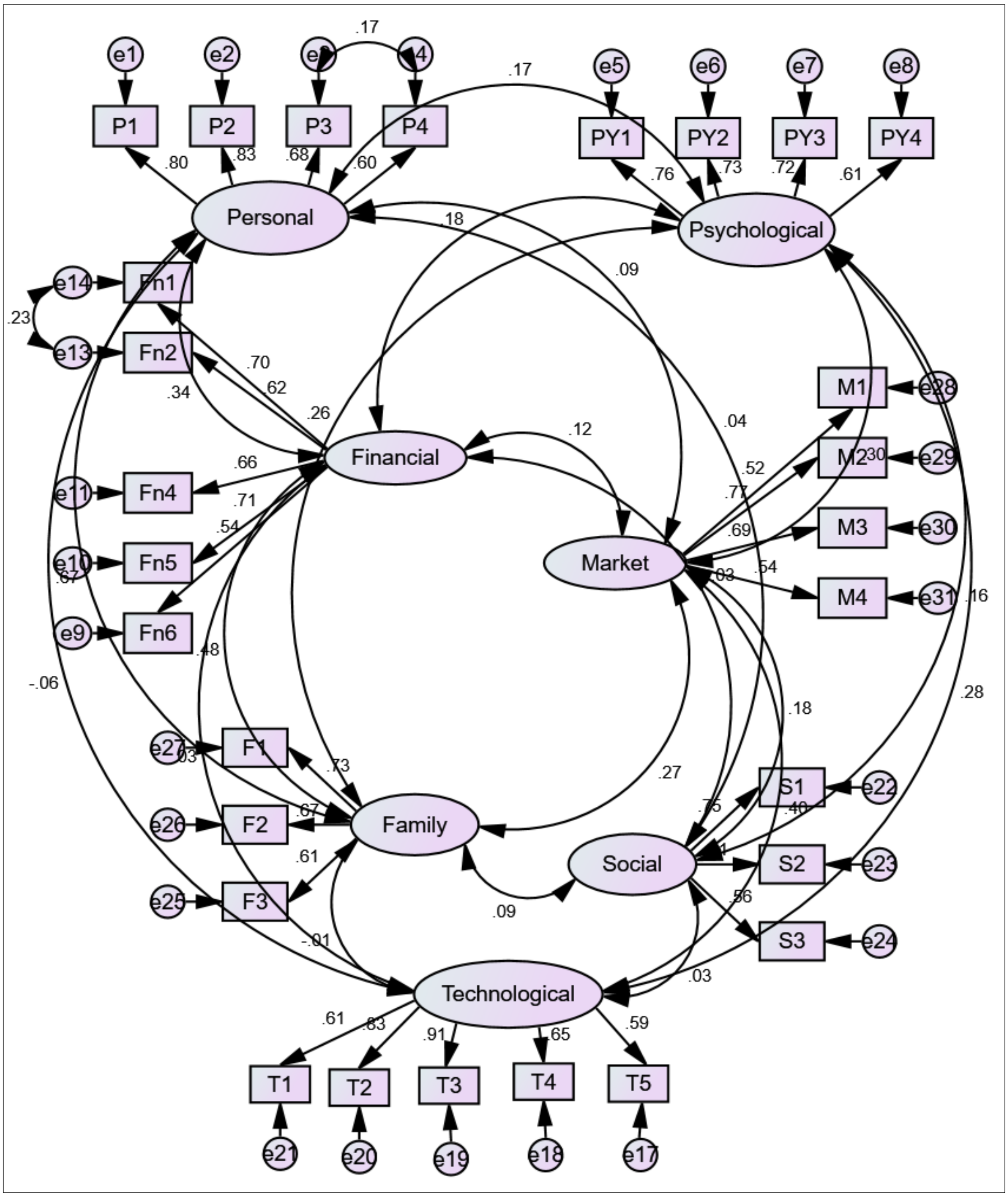

Fig. 2. Risk aversion model.

Table 2. Model fit summary for risk aversion model

S.No.	Type of model fit	Test	Recommended value	Values
1.		Likelihood ratio Chi-square(χ^2)	Insignificant χ^2 (p>0.05) (12)	544.04** (DF=327)
2.		Normed chi-square(χ^2/df)	χ^2/df <3 (10)	1.664
3.	Absolute fit measures	Goodness-of-Fit Index (GFI)	GFI>0.90 (11)	0.904
4.		Adjusted Goodness of Fit Index (AGFI)	AGFI >0.90 (10)	0.880
5.		Root Mean square Residual (RMR)	RMR <0.05 (10)	0.050
6.		Root Mean Squared Error of Approximation (RMSEA)	RMSEA <0.08 (10)	0.043
7.		Normed Fit Index (NFI)	NFI >0.90 (11)	0.856
8.	Incremental fit measures	Incremental fit index (IFI)	IFI =Values close to 1 (10)	0.937
9.		Tucker-Lewis Index (TLI)	TLI>0.90 (10)	0.926
10.		Comparative Fit Index (CFI)	CFI>0.90 (12)	0.936
11.		Parsimonious Goodness of Fit Index (PGFI)	PGFI>0.50 (12)	0.728
12.	Parsimonious fit measures	Parsimonious Normed Fit Index (PNFI)	PNFI>0.50 (12)	0.741
13.		Parsimonious Comparative Fit Index (PCFI)	PCFI>0.50 (12)	0.810

Although some incremental fit indices, such as NFI (0.856) and AGFI (0.880), fell slightly below the commonly recommended thresholds, they were still within a tolerable range for exploratory studies in social science research. More importantly, the model demonstrated strong performance across other key indices: the Normed Chi-square (1.664), RMSEA (0.043) and CFI (0.936) all indicated a satisfactory fit. Together with a Cronbach's alpha of 0.804, which confirmed high internal consistency, these results suggested that the measurement model was both reliable and robust. Therefore, despite minor deviations in certain indices, the model was considered acceptable for examining risk aversion among farmers in the study area.

During the iterative fitting process, specific items were eliminated due to non-significant loading. These included one item in the financial factor, two in the technological factor and two in the market factor. Covariance analysis revealed significant relationships between factors. From Table 3, the covariance value between Personal and Psychological factors was 0.105, suggesting that personal factors influence farmers' risk resilience strategies. Similarly, a covariance value of 0.324 between Personal and Family factors indicated the strong influence of family on farmers' decisions. Covariances among other factors also showed significant relationships, such as Market and Technological (0.09), Social and Market (0.05) and Family and Market (0.06).

The Average Variance Extracted (AVE) for all constructs was above 0.5, indicating adequate convergent validity, while Construct Reliability (CR) values exceeding 0.7 confirmed the constructs' reliability.

Factor-Specific Results

Table 4 depicts the standardized regression weights of risk aversion factors.

1. Personal factor

Standardized coefficients for Personal Factor items, including demise of elder family members (0.797) and dissension among family members (0.829), indicated a strong influence on farmers' risk aversion strategies. Dissension among family members had the highest effect, emphasizing its critical role.

2. Psychological factor

Psychological factors such as conflict among peer farmers (0.756) and disagreements within families (0.73) significantly influenced farmers' risk aversion. The standardized coefficients highlighted how psychological stressors shaped risk-related decisions.

3. Financial factor

Loss of income due to events such as floods (0.707) and delayed insurance disbursements (0.662) were significant contributors to risk aversion. The financial strain from natural calamities emerged as a critical determinant.

4. Social factor

Weaker linkages between farmers and social institutions (0.811) and disputes over water issues (0.558) demonstrated the role of social dynamics in influencing risk behaviour.

5. Family factor

Health status of family members (0.727) and the pressure from aging relatives (0.668) significantly drove risk aversion among farmers, with health-related expenditures playing a pivotal role.

6. Market factor

Lack of infrastructure in markets (0.774) and increased transportation costs (0.685) were prominent issues influencing market-related risks.

7. Technological factor

Adverse outcomes from adopting new technologies (0.907) and insufficient technical guidance (0.648) significantly affected technological risk aversion.

Discussion

Fig. 3 & Table 5 depict the structural model and highlight the significant influence of various factors on farmers' risk behaviour. The significant t-statistic values for the paths Family → Risk behaviour (4.186), Psychological → Risk behaviour (4.807) and Technological → Risk behaviour (2.855) confirmed their relevance in explaining risk aversion strategies.

Table 3. Covariance's among risk aversion factors

S. No.	Covariance's			Estimate	S.E.	C.R.	P
1.	Personal	<-->	Psychological	**0.105**	0.04	2.634	0.008**
2.	Personal	<-->	Financial	**0.147**	0.033	4.499	***
3.	Personal	<-->	Technological	-0.031	0.029	-1.063	0.288
4.	Personal	<-->	Social	0.021	0.038	0.56	0.575
5.	Personal	<-->	Family	**0.324**	0.045	7.125	***
6.	Personal	<-->	Market	0.035	0.025	1.415	0.157
7.	Psychological	<-->	Financial	**0.061**	0.023	2.628	0.009**
8.	Psychological	<-->	Technological	**0.106**	0.025	4.173	***
9.	Psychological	<-->	Social	**0.074**	0.031	2.427	0.015*
10.	Psychological	<-->	Family	**0.097**	0.027	3.53	***
11.	Psychological	<-->	Market	**0.086**	0.022	3.962	***
12.	Financial	<-->	Technological	0.008	0.017	0.509	0.61
13.	Financial	<-->	Social	-0.011	0.022	-0.492	0.623
14.	Financial	<-->	Family	**0.127**	0.025	5.162	***
15.	Financial	<-->	Market	0.025	0.014	1.739	0.082
16.	Social	<-->	Technological	0.011	0.022	0.475	0.635
17.	Family	<-->	Technological	-0.004	0.019	-0.197	0.844
18.	Market	<-->	Technological	**0.09**	0.019	4.833	***
19.	Social	<-->	Family	0.033	0.025	1.3	0.193
20.	Social	<-->	Market	**0.05**	0.02	2.54	0.011*
21.	Family	<-->	Market	**0.06**	0.018	3.36	***

Table 4. Standardized regression weights of risk aversion factors

Regression weights			Factor loading (FL)	Item Reliability (IR)	Delta	AVE	Sum of FL	Sum of Delta	CR
P1	<---	Personal	0.797	0.635	0.365				
P2	<---	Personal	0.829	0.687	0.313				
P3	<---	Personal	0.681	0.464	0.536				
P4	<---	Personal	0.604	0.365	0.635	0.538	2.911	1.849	0.821
PY1	<---	Psychological	0.756	0.572	0.428				
PY2	<---	Psychological	0.73	0.533	0.467				
PY3	<---	Psychological	0.72	0.518	0.482				
PY4	<---	Psychological	0.606	0.367	0.633	0.498	2.812	2.010	0.797
Fn6	<---	Financial	0.538	0.289	0.711				
Fn5	<---	Financial	0.707	0.500	0.500				
Fn4	<---	Financial	0.662	0.438	0.562				
Fn2	<---	Financial	0.623	0.388	0.612				
Fn1	<---	Financial	0.699	0.489	0.511	0.421	3.229	2.896	0.783
S1	<---	Social	0.745	0.555	0.445				
S2	<---	Social	0.811	0.658	0.342				
S3	<---	Social	0.558	0.311	0.689	0.508	2.114	1.476	0.752
F3	<---	Family	0.608	0.370	0.630				
F2	<---	Family	0.668	0.446	0.554				
F1	<---	Family	0.727	0.529	0.471	0.448	2.003	1.656	0.708
M1	<---	Market	0.519	0.269	0.731				
M2	<---	Market	0.774	0.599	0.401				
M3	<---	Market	0.685	0.469	0.531				
M4	<---	Market	0.542	0.294	0.706	0.408	2.52	2.369	0.728
T5	<---	Technological	0.588	0.346	0.654				
T4	<---	Technological	0.648	0.420	0.580				
T3	<---	Technological	0.907	0.823	0.177				
T2	<---	Technological	0.834	0.696	0.304				
T1	<---	Technological	0.605	0.366	0.634	0.530	3.582	2.350	0.845

Table 5. Hypothesis testing in the structural model of risk aversion

S. No.	Hypothesis	Sample mean (M)	Standard deviation (STDEV)	T statistics	P values
H_{1b}	Family -> Risk behaviour	-0.234	0.055	**4.186**	**0.000**
H_{2a}	Financial -> Risk behaviour	0.004	0.137	0.664	0.507
H_{3a}	Market -> Risk behaviour	0.102	0.111	1.156	0.248
H_{4a}	Personal -> Risk behaviour	-0.095	0.053	1.429	0.153
H_{5b}	Psychological -> Risk behaviour	0.215	0.045	**4.807**	**0.000**
H_{6a}	Social -> Risk behaviour	-0.131	0.084	1.790	0.074
H_{7b}	Technological -> Risk behaviour	0.131	0.041	**2.855**	**0.004**

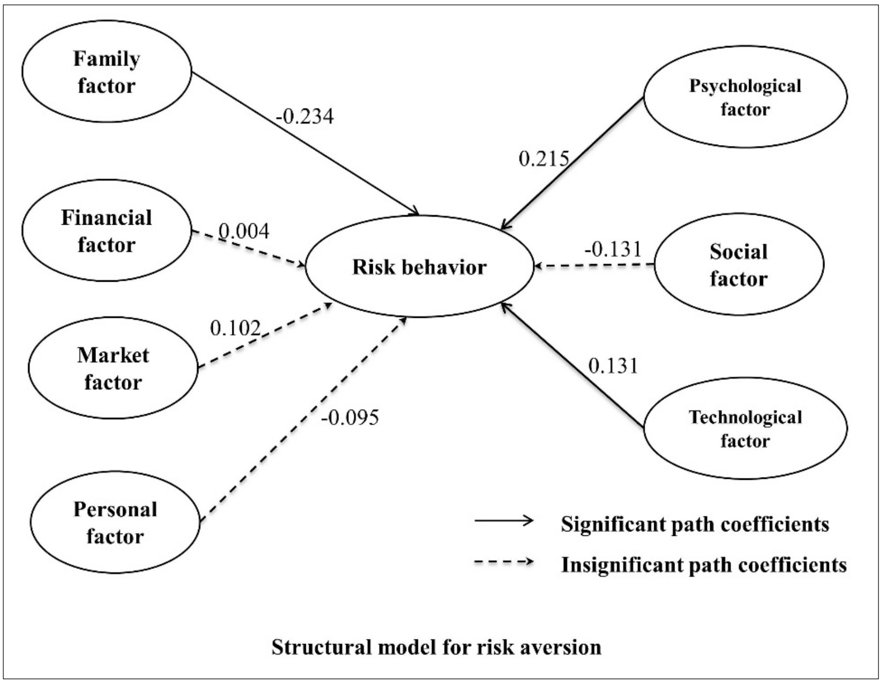

Fig. 3. Structural model for risk aversion.

The findings suggested that family dynamics, including support and health-related factors, played a vital role in shaping farmers' decisions. The psychological factors reflected the critical impact of social interactions and stress on adaptive strategies, though their influence on risk behaviour was inconsistent across contexts. Technological factors, particularly adverse outcomes from technology adoption, underscored the need for better technical support and follow-up mechanisms to improve farmers' confidence in resilient strategies.

These results aligned with global evidence that family and health-related risks were among the most frequently perceived risks shaping adaptive choices (13-15). Similarly, psychological and social perceptions remained central to farmers’ decisions under uncertainty, although their strength varied depending on socioeconomic and institutional contexts (16). The technological challenges reported in this study were also consistent with findings from China, where limited technical support constrained the adoption of climate-smart practices despite high-risk awareness (17).

At the same time, this study diverged from global patterns regarding financial and market risks. While many studies highlighted price fluctuations, access to credit and market volatility as dominant concerns (16, 18), the farmers in the study area appeared to normalize these constraints as part of their regular environment. This finding suggested that, unlike in developed contexts where financial and market risks actively shaped behaviour, in this region, they may have exerted a weaker influence because of long-term adaptation to persistent uncertainty.

The implication for policymakers was that simply improving financial services or market access might not have automatically translated into changes in farmers’ risk behaviour unless these measures were coupled with stronger family support systems, psychological resilience-building and the promotion of adaptive technologies. This supported recommendations that risk management interventions be holistic, integrating social, technological and institutional elements (15).

Overall, the study underscored the multifaceted nature of risk aversion among farmers and the interplay between personal, psychological, financial, social, market and technological factors in shaping resilience strategies. By situating these findings within global evidence, it became clear that while certain risk drivers were universal (e.g., family and psychological factors), others (such as financial and market challenges) were locally contextualized and required tailored policy responses.

Conclusion

This study highlighted the multidimensional nature of risk aversion among farmers in the Cauvery Delta, where personal, family, psychological, technological, social, financial and market factors interacted to shape risk behaviour. The results demonstrated that higher levels of risk aversion were associated with greater adoption of risk management strategies, yet knowledge gaps and structural constraints limited the extent of their implementation. Crop insurance emerged as the most preferred strategy, underscoring the importance of institutional support in enabling farmers to manage uncertainties effectively.

For policy and practice, the findings suggested that empowering farmers required more than individual awareness or willingness to adopt risk management measures. Governments must strengthen crop insurance schemes through simplified procedures, timely claim settlements and digital access, while NGOs and extension agencies should have enhanced farmers’ knowledge and confidence through training, awareness campaigns and practical demonstrations. Extension workers also played a critical role in promoting climate-resilient practices, diversification and efficient resource use. By aligning institutional interventions with farmers’ behavioural tendencies, stakeholders could have built a more resilient agricultural system that reduced vulnerability, enhanced livelihoods and ensured sustainable development in risk-prone regions.

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Authors' contributions

VM designed the research framework, conducted the field survey, contributed to manuscript writing and overall research work. PB performed critical revisions and finalized the manuscript. MS assisted with the data analysis and contributed to drafting sections of the manuscript. SK provided technical inputs and reviewed the final draft. GD assisted in field data collection, literature review and initial data compilation. All authors read and approved the final manuscript.

Compliance with ethical standards

Conflict of interest: The authors declare that they have no conflicts of interest.

Ethical issues: None

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used OpenAI for language editing and to refine the structure of the manuscript. Following the use of this tool, the authors thoroughly reviewed and edited the content as necessary and take full responsibility for the final version of the publication.

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