Discover Sustainability

RESEARCH Open Access

Understanding shrimp farmer preferences on index-based insurance as a risk mitigation tool in the Mekong Delta

Vo Hong Tu[1], Nguyen Thuy Trang[1*], Hisako Nomura[2] and Yoshifumi Takahashi[2]

*Correspondence:
Nguyen Thuy Trang
nttrang@ctu.edu.vn
[1]Department of Rural Socio-Economics, College of Rural Development, Can Tho University, Can Tho, Vietnam
[2]Faculty of Agriculture, Kyushu University, Fukuoka, Japan

Abstract

Shrimp farming in the Mekong Delta faces significant market and climate risks, including disease outbreaks, extreme weather, and water quality fluctuations, leading to financial losses. Index-based insurance offers a potential risk management solution. This study investigates shrimp farmers' willingness to pay for key insurance attributes using a latent class choice model and survey data from 500 farmers in major aquaculture regions. The analysis identifies two distinct segments. Segment 1 (low-education, training-responsive) favors early payout and seasonal coverage, but resists company-assisted claims, preferring transparent processes like self-assessment or participatory verification. Trust-building through training is key for this group. Segment 2 (higher-education, company-trusting) accepts company involvement and weather-based assessments, with moderate WTP for structured or bundled packages, especially when pricing is transparent and service reliable. Outreach for this group should emphasize provider credibility over training. The results suggest that customized insurance products are more effective than a one-size-fits-all approach. Insurers and policymakers should develop flexible policies tailored to farmers' risk perceptions and financial capacities.

Keywords Shrimp farming, Index-based insurance, Willingness to pay, Latent class choice model, Risk management

JEL Classification C91, D15, G22, O13

1 Introduction

Agricultural production holds a pivotal position in the socio-economic development of Vietnam, supporting the livelihoods of more than 60% of the population engaged in agriculture and fisheries. According to the General Statistical Office—[22], the total fishery production in 2023 was estimated at approximately 8423 thousand tons. The average annual growth rate of fishery production from 1995 to 2023 remained consistently at 8%. In 2023, the shrimp farming area covered approximately 736.5 thousand hectares, leading to a total production of about one million tons.

© The Author(s) 2025. **Open Access** This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.

The Mekong Delta (MD) serves as a prominent center for aquaculture, with a specific focus on brackish water shrimp [22]. In 2022, the brackish water shrimp farming area was estimated to encompass about 697.32 thousand hectares with a corresponding total export value exceeding 4.3 billion USD. Despite facing challenges in 2023 due to global market competition, the total shrimp export turnover for Vietnam is around 3.4 billion USD. This underscores the pivotal role of the shrimp sector as a fundamental driver for both the Vietnamese economy and the MD.

Previous studies reported that the MD is one of the three deltas in the world most affected by climate change [26, 27]. Climate change leads to rising temperatures and severe salinity intrusion in the coastal areas [11, 50, 66]. In addition, the volatilities of input and output markets have impelled farmers to transform their farming activities (including crop diversification, farming calendar changes and shift from extensive to intensive farming) inevitably to adapt, especially in coastal areas [7, 13]. However, in the context of climate change, disease outbreaks, and market instability, significant risks have emerged for agricultural producers [34, 36, 57, 60, 61, 63]. These challenges not only threaten food security but also jeopardize the livelihoods of millions reliant on agriculture for their income and sustenance. Therefore, examining risk management strategies at the farm level, with a specific focus on insurance for shrimp farmers, is crucial for proposing solutions that promote sustainable agricultural production, and climate change adaptation.

One of the promising risk management strategies in agriculture is parametric agricultural insurance. It is a type of insurance that pays out benefits based on a predetermined index (e.g., rainfall level) for loss of assets and investments, primarily working capital, resulting from weather and catastrophic events, rather than indemnifying the actual losses incurred by the insured [12, 28, 46]. Climate index-based insurance, which could be called weather derivative, parametric insurance, or weather insurance, is particularly relevant in agriculture, where traditional insurance models based on assessing and compensating for actual losses can be challenging due to the complex and variable nature of agricultural risks. Governments have promoted agricultural insurance through the private sector, often with government financial support (public–private partnerships) since the 1990s [41]. It has comparative advantages, such as quicker payout times and lower administrative costs, and limitations, like the potential mismatch between index triggers and actual damages experienced by farmers [59]. It reduces some potential hazards containing traditional damage-based insurance, such as high administrative costs, delayed payouts, and complexity and lack of transparency over the insurance process. Despite these advantages, the uptake of index-based insurance has been low, primarily due to basis risk. This refers to the situation where the payouts from index insurance are too low to adequately compensate for the losses farmers incur [12, 29]. In Vietnam, for example, farmers participating in some index-based pilot programs have expressed dissatisfaction with payouts that were insufficient to cover their losses [52]. The rise of parametric agricultural insurance in regions like Southeast Asia, Africa, and Latin America presents unique challenges and opportunities. While the model promises efficiency, the low uptake of the insurance remains a critical concern, largely due to basis risk. The mechanism behind the uptake of such insurance needs to be understood in order to address the reasons behind low participation.

Furthermore, index-based insurance is urgently needed for specific products that are vulnerable to natural catastrophes due to changes in the environment. The global review of climate index-based insurance found that the insurance's main target commodities were widely among but limited to cereal crops and protection against drought, but agricultural climate index-based insurance should be available and beneficial in managing other commodities and climate risks [1]. Therefore, establishing an index insurance targeting a specific commodity and the type of risk for farmers undergoing agriculture transformation due to climate change is urgently required. Under the context of climate change and agricultural structuring, the farmers have been facing a set of challenges. To deal with these risks, it is essential to implement parametric insurance to transfer risks and mitigate the risks for farmers in general and shrimp farmers in particular.

The findings of this study identify two distinct segments of shrimp farmers with significantly different preferences regarding key attributes of index-based insurance, revealing pronounced heterogeneity in both attitudes toward risk and WTP. Farmers in Segment 1 (Training-responsive, price-sensitive farmers with low education) exhibit a strong WTP for extended and seasonal coverage, underscoring their heightened concern for long-term production risks amid growing climate threats in the MD [6, 60]. However, this group is less favorable toward weather-based loss assessments and company-assisted claims, possibly due to trust or autonomy concerns. In contrast, Segment 2 (Company-trusting, moderately price-sensitive farmers with higher education) demonstrates a lower WTP for extended coverage but shows a strong preference for structured, company-assisted claim processes and accepts weather-indexed assessments—highlighting their desire for procedural clarity and reliability. The identification of training responsiveness as a key determinant of insurance adoption potential—particularly among lower-education farmers—highlights an actionable pathway for increasing uptake through targeted capacity—building. Moreover, the finding that early payout preferences are segment-specific, rather than uniform across farmers, adds new nuance to the discourse on temporal alignment between insurance benefits and production cycles.

These findings yield several novel contributions to the literature on agricultural risk management and insurance in transformed aquaculture systems. First, from a methodological perspective, this is one of the first studies in Vietnam—and the broader MD region—to apply latent class choice modeling (LCCM) to segment shrimp farmers based on their insurance preferences. While choice modeling (CM) has been widely applied in consumer research and ecological valuation [8, 10, 20], and has seen increasing use in crop insurance contexts [24, 54], its application in aquaculture insurance—especially in emerging economies—remains limited. In Vietnam, most prior studies on agricultural insurance [33, 34, 57] have relied on contingent valuation or regression-based approaches, often assuming homogenous preferences across farmers. This study extends methodological frontiers by capturing unobserved heterogeneity in insurance adoption behavior using repeated choice sets and utility-based modeling grounded in Lancaster's theory of value [37, 40, 43].

Second, empirically, this research directly addresses the rising vulnerability of transformed shrimp farming systems to climate shocks such as salinity intrusion, temperature rise, and disease outbreaks [60, 61]. In this context, insurance remains underdeveloped due to issues of asymmetric information, moral hazard, and inappropriate product design [14, 30]. The study adds new insights by showing how shrimp farmers' risk

attitudes—shaped by socioeconomic factors and exposure to environmental shocks—lead to divergent preferences for insurance design features, such as coverage length, claim assistance, and loss assessment mechanisms. This empirical heterogeneity underscores that a uniform insurance scheme is unlikely to meet the needs of all producers, particularly in high-risk, highly diversified agricultural landscapes like the MD.

Overall, this study makes two critical contributions. It (1) introduces a segmentation-based analysis of insurance preferences in aquaculture, advancing the methodological toolkit for non-market valuation in risk-prone farming sectors, and (2) provides empirical evidence of preference heterogeneity linked to production realities, supporting the case for tailored, farmer-centered insurance designs. These insights are especially relevant for scaling climate-resilient insurance programs under Vietnam's agricultural restructuring strategy and in light of global experiences in adaptive risk management [23, 38, 65].

The paper is structured as follows. The next section reviews relevant literature on index-based insurance and its role in enhancing resilience within the aquaculture sector, particularly shrimp farming. This is followed by a description of the research methodology, including survey design, data collection, and the use of latent class choice modeling to capture heterogeneity in farmer preferences. The subsequent section presents the empirical findings and discusses the key factors influencing farmers' adoption of index-based insurance. The final section offers concluding remarks, policy implications for strengthening climate resilience through insurance, and suggestions for future research in aquaculture risk management.

2 Literature review

2.1 About risks of transformed agricultural production

According to Bernstein et al. [6], the MD is among the three most climate-vulnerable deltas globally, alongside the Ganges–Brahmaputra (Bangladesh) and Nile (Egypt). Climate change and sea level rise scenarios in Table 1 indicate that the MD faces rising temperatures (0.67 °C over 61 years), with projections of a 1.3–1.5 °C increase by 2050 and up to 3.5 °C by 2100 under RCP 8.5 [48, 60]. Sea level rise poses serious threats: with a 100 cm rise, 38.9% of the MD could be inundated, especially coastal provinces like Kien Giang (76.9%), Ca Mau (57.7%), and Soc Trang (50.7%). Hau Giang, an inland province, is also at high risk (80.6%).

By 2100, the average temperature will increase by 1.7–1.9 °C. According to the RCP 8.5 scenario, by the end of 2100, the regional temperature will increase by about 3.3–3.5 °C. Similarly, the maximum and minimum temperatures also tend to increase, on average about 1.6–2.7 °C under the RCP 4.5 scenario. Precipitation also tends to increase from 5 to 15% under two scenarios by 2050. Salinity intrusion is worsening, notably during the 2019–2020 dry season, affecting 10/13 provinces and 42.5% of the MD's natural land. Ca Mau experienced significant damage, with 14,000 ha of crops severely affected.

Table 1 Predicted effects of salinity intrusion in the MD

No	Indicators	Projected sea level rise	
		50 cm	100 cm
1	Population affected (%)	10	35
2	Total land affected (%)	4.48	38.9
3	GDP reduced (%)		10

Alongside salinity and climate risks, transformed agricultural models in coastal areas face additional challenges such as low-quality breeds, disease outbreaks, market instability, input price volatility, and limited information access [61].

2.2 About risk management of transformed agricultural production

2.2.1 About risk management strategies

In order to have a basis for proposing risk management strategies, it is necessary to learn farmers' attitudes towards risks, risk magnitude, and risk management strategies. According to Walker and Jodha [65], an individual's attitude towards risk is expressed through a prudent attitude in making investment decisions, and using resources for production activities. Different individual has different economic, social, environmental and natural characteristics, so his/her perception of risk is also different from each other, resulting in different risk management strategies [55]. Therefore, many previous studies have classified households into the following three groups: the risk-averse, the risk-taking, and the risk-neutral groups. Risk-averse households often prefer options that produce a secured outcome, although the outcome can be much lower than risky options [18]. According to Walker and Jodha [65], poor farmers are often afraid of risks because they cannot cover their household expenses if they fail in their crops. These results suggested that the risk management strategies are different among households. Thus, it is required to consider the heterogeneity when designing interventions or providing support.

According to Harwood [23], Huirne et al. [25], risk management strategies can be divided into two groups: (1) the first is on-farm risk management strategies, and (2) the second is the strategies to share risks with others. In particular, the on-farm risk management strategies often include specific activities/solutions such as: (1) collecting more information to support the decision-making process, (2) avoiding or reducing exposure to risk; (3) choosing less risky technology; (4) diversifying production activities; (5) flexibility in response and adaptation. The strategies to share risks with others include the following specific solutions: (1) farm financing; (2) production insurance; (3) contract marketing and futures trading.

In this study, production risk management strategies will be considered to incorporate into one-step estimation of stochastic frontier production function and flexible risk function as well as in ordered logit to identify factors affecting the farmer's level of risk. For risk-sharing strategies, farm financing, as well as contract marketing and futures trading, have been widely implemented in Vietnam in general and in the MD in particular. However, regarding agricultural insurance, especially for transforming agriculture, there has been no research carried out. Therefore, the study focuses on investigating the preferences of transformed farmers on agricultural insurance, from which one can design and investigate the feasibility of the attributes as well as characteristics of the agricultural insurance by using the CM.

2.2.2 About insurance for agricultural production and transformation

The MD is a key agricultural producer, bearing national food security. However, the climate change, epidemics and market instability have caused many risks for agricultural households [35, 36, 57, 60, 61]. According to Kiet and Phat [31]; Le and Pham [38], farmers are often afraid of risks and will therefore try to avoid or mitigate risks through risk

management strategies. Agricultural insurance is considered one of the effective risk reduction strategies that many scientists are interested in and promoted the practical application [23, 25]. According to Ellis and McGuire [18]; Patil and Veettil [51], risk-averse farmers are more reluctant or slow to apply new scientific and technical advances than other farmers, even though these farmers know that such application can improve their productivity and income. Therefore, helping to create a more certain environment will help farmers feel secured to invest and then contribute to improving the efficiency of production activities.

According to Khoi and Hiep [34], in the undeveloped market of insurance, people's participation in agricultural insurance will be limited and the insurance supply will also be limited due to asymmetric information between buyer (farmer) and seller (insurance company). Information asymmetry leads to two major problems in the agricultural insurance market, i.e. insurability and moral hazard [14]. Insurability refers to a situation in which households with a high level of risk are more likely to participate in insurance, leading to the unaffordability of insurance companies and the limited number of companies entering the insurance market [30]. If the premium is increased to cover compensation, the number of participants will decrease, and only those with high-risk levels will participate. Moral risk is related to changing production behavior in order to increase the probability of damage or increase the severity of damage in order to receive compensation, which increases the cost of monitoring, supervision, assessment, and compensation [14].

Agricultural insurance (damage-based) in Vietnam, in general and the MD, in particular,, has been piloted since 2011 according to Decision No. 315/QĐ-TTg promulgated on March 1, 2011, by the former Prime Minister on the implementation of the pilot program on agricultural insurance for the period 2011–2013 in 20 provinces. In the MD, insurance for rice was implemented in An Giang and Dong Thap provinces and insurance for aquaculture (catfish, tiger shrimp, white-leg shrimp) in Ben Tre, Soc Trang, Tra Vinh, Bac Lieu, Ca Mau. To continue the program, the government issued Decree No. 58/2018/ND-CP on April 18, 2018 on agricultural insurance. The prime minister has also issued Decision No. 22/2019/QĐ-TTg on implementing subsidy policies for agricultural insurance, which facilitating farmers to buy agricultural insurance to minimize damages due to natural disasters and epidemics.

Although the agricultural insurance program has brought many positive impacts on farmers' income as well as changed farmers' perceptions of risk management tools, the proportion of households participating in insurance is still quite limited. Due to the fact that the insurance packages are not close to reality, the process of determining the damages was not consentaneous between farmers and insurance companies and the procedure for compensation is still quite complicated [33–36, 57]. In addition, there has been no insurance package so far designed specifically for transformational farmers, while agricultural restructuring programs adapting to climate change have been paid attention to and implemented widely.

2.2.3 About application of choice modelling for designing insurance package

In theory, there have been many different approaches to determining farmers' preferences and willingness to pay. CM is one of the methods widely employed in many different fields to determine the marginal willingness to pay for a product/service that do not

have market prices, including tourism and ecological services [8, 20]. Many marketing studies also employed this approach to understand the tastes and willingness of consumers to pay for each product's attributes.

CM is an approach based on stated preference. This method is derived from a combined analysis; the interviewees (farmers in this case study) will be faced with many choice sets. From each choice set, the farmer chooses the most preferred option. By assigning a price to each alternative, estimates of marginal benefit can be converted into monetary values for each change in the attribute's level [47]. Then, the probability that farmer i selects alternative j in a choice set over n alternatives is perceived as the probability of the utility obtained from alternative j is greater than the probability of the utility from the other alternatives. This method allows multiple choice sets to be selected through repeated properties and scenarios (instead of having trade-offs as in the contingent evaluation method—CVM), allowing us to test and the farmers to express their "true" preferences. To study the transformed farmers' preferences on agricultural insurance, especially attributes such as types of damages/diseases covered, rate of compensation, insured crops, complexity of claim procedures and premium rates, …, the proposed study will employ a discrete choice modelling developed by Louviere et al. [40]. This method has been widely used to estimate the non-market value of goods [8, 58, 62, 64].

According to Lancaster's economic theory, a product (insurance package) that a farmer is willing to buy includes different attributes [37]. To value these attributes, the previous studies put them in the choice sets to be selected by buyers [43]. Such selection reflects the indirect utility of farmers for different attributes across different scenarios.

Regarding the application of the CM method to determine people's preferences on insurance, although there have been few previous studies using this approach in Vietnam, many international studies have been done, such as Huang et al. [24] studied insurance packages for potato farmers, Sibiko et al. [54] studied weather insurance for small-scale farmers, Ye et al. [68] considered about the liabilities and supports for agricultural insurance, Liesivaara and Myyrä [39] studied willingness to pay for crop insurance in northern Europe; Brouwer and Akter [10] studied about micro insurance packages to reduce the risk of weather disasters. The domestic studies on agricultural insurance mainly employed the CVM approach or logit/probit regression. Such practical applications include the studies of [33–36, 57].

3 Method

3.1 Attributes and study design

The selection of insurance attributes in this study is based on key factors influencing shrimp farmers' decision-making regarding index-based insurance, as determined through an extensive literature review. To ensure the attributes used in the choice experiment are valid and relevant, the research team conducted key informant interviews and focus group discussions with experts, local authorities and shrimp farmer groups. These engagements provided valuable insights into farmers' preferences, particularly their strong preference for insurance premiums and coverage based on total revenue losses rather than production costs. This preference aligns closely with actual farming practices and household financial planning, making it highly relevant for index-based insurance. Given that intensive, semi-intensive, and extensive farming systems differ in costs, yields, and market prices—leading to significant variation in revenue—we recommend

calculating insurance premiums as a percentage of each household's actual or projected revenue. This revenue-based approach promotes fairness and affordability by aligning premiums with farmers' income levels and risk exposure, making it more suitable for diverse shrimp farming contexts.

Furthermore, to ensure the attributes are practical and aligned with insurance industry practices, the research team conducted in-depth interviews with Bao Viet Insurance, one of leading agricultural insurers in Vietnam. These interviews provided a comprehensive understanding of current practices in claim procedures, loss assessment, and premium structures. The consultations confirmed that the selected attributes are realistic, market-relevant, and reflective of both farmers' needs and industry standards.

Due to the constraints of discrete choice modeling and the requirements of orthogonal experimental design, the number of attributes included in the final choice sets was limited. This trade-off is inherent in choice experiment methodology: while incorporating more attributes could provide richer preference data, it risks overwhelming respondents, thereby reducing response reliability. Consequently, certain potentially significant attributes, such as government subsidies or farmers' willingness to accept insurance under varying support scenarios, were excluded from the choice sets. The research team recognizes this limitation and plans to address it through complementary survey components or follow-up studies to explore these aspects in greater depth. The attributes were carefully selected to address the most critical aspects of risk coverage, financial feasibility, and accessibility, ensuring the proposed insurance product meets the needs and constraints of shrimp farmers. The rationale for each attribute is as follows:

Insurance coverage start time

Shrimp farming is highly vulnerable to disease outbreaks and environmental fluctuations, particularly in the early stages of cultivation. Insurance companies often limit their coverage to later stages to mitigate excessive risk exposure. Therefore, this attribute examines farmers' preferences for different coverage start times—40, 50, or 60 days after stocking—allowing an assessment of how farmers perceive risk at different growth stages and their willingness to adopt delayed insurance coverage [69].

Insurance coverage duration

Shrimp farming cycles vary, with some farmers operating on a seasonal basis while others engage in year-round production. To address these variations, two insurance package options are considered: seasonal coverage (tailored to individual production cycles) and annual coverage (providing long-term risk mitigation). This attribute helps determine whether farmers prefer flexibility in short-term protection or a more comprehensive long-term insurance plan [19].

Loss assessment method

One of the critical challenges in index insurance is defining a transparent and objective mechanism for determining losses [15]. Two primary methods are evaluated:

- Weather-based assessment, which relies on external climate or environmental indicators to trigger payouts.
- On-site farm/pond evaluation, which involves direct assessment of shrimp losses at the farming site.

This attribute allows an analysis of farmers' trust in indirect (index-based) assessments versus traditional loss verification approaches.

3.1.1 Claim procedures

The ease of processing insurance claims significantly impacts farmers' willingness to adopt insurance [17, 33]. Two options are examined:

- Self-processed claim procedures, where farmers handle documentation independently.
- Insurance company-assisted procedures, where companies provide guidance and support.

This attribute evaluates farmers' preferences for simplicity and administrative support when seeking compensation.

3.1.2 Insurance premium rate

The financial feasibility of insurance is a crucial determinant of participation. The premium rate is set as a percentage of farmers' average revenue, with four levels: 0.5%, 1%, 1.5%, 2%, and 2.5%. This attribute helps assess farmers' price sensitivity and their willingness to pay for risk protection, providing insights into the optimal pricing structure for widespread adoption. The summary of attributes and the levels of each attribute are presented in Table 2 below:

We applied an orthogonal design using SPSS® software to generate a minimal set of 25 discrete profiles for index insurance options in shrimp farming. Given the nature of the insurance attributes, a cyclical or foldover design was employed to maintain frequency balance across attribute levels [40]. In this approach, the levels of an added attribute were systematically adjusted based on the previous alternative within the same choice set to ensure statistical efficiency.

To develop the choice sets, key attributes influencing shrimp farmers' insurance preferences were identified through a survey, ensuring that the selected attributes reflected real-world insurance options. These attributes and their levels encompassed various features relevant to index-based insurance for shrimp farming (see Table 2). To streamline the survey, the 25 choice sets were randomly divided into five versions of the questionnaire, with each respondent evaluating five choice sets (the example choice set is

Table 2 Attributes and levels for index insurance package

Attribute	Description
Insurance coverage start time	To ensure a balanced benefit-sharing approach with insurance companies, coverage is only provided after the first 40 days of shrimp stocking due to the high risks in the initial stage. This attribute considers three coverage durations: (1) 40 days after stocking, (2) 50 days after stocking, and (3) 60 days after stocking
Insurance coverage duration	This attribute includes two options: (1) Seasonal insurance package and (2) Annual insurance package
Loss assessment method	There are two approaches for determining losses under this attribute: (1) Loss assessment using weather-based indicators (2) Loss assessment through on-site farm/pond evaluation
Claim procedures	This attribute refers to the process of completing insurance claim documentation and offers two methods: (1) Self-processed claim procedures (2) Insurance company-assisted claim procedures
Insurance premium rate	The premium is calculated based on the average revenue of the shrimp farming model, with four levels: 0.5%, 1%, 1.5%, 2%, and 2.5% of total revenue

presented in Appendix 1). The questionnaires were then randomly distributed to shrimp farmers. The study collected responses from a total of 500 participants, resulting in 2500 recorded individual choices.

3.2 Data collection

The MD comprises eight coastal provinces engaged in shrimp farming, including Long An, Tien Giang, Ben Tre, Tra Vinh, Soc Trang, Bac Lieu, Ca Mau, and Kien Giang. According to statistical data from the General Statistics Office [22], total shrimp production in the region has experienced significant growth over the past two decades (Table 3). From a modest 265.76 thousand tons in 2005, shrimp production surged to more than 1 million tons in 2023, representing an average annual growth rate of 7.64%. Among the eight provinces, the four leading shrimp-producing provinces—Soc Trang, Bac Lieu, Ca Mau, and Kien Giang—accounted for a combined 75.88% of the Mekong Delta's total shrimp production in 2023. Ca Mau alone contributed the highest share (23.14%), followed by Bac Lieu (20.70%), Soc Trang (20.05%), and Kien Giang (11.99%). These provinces have consistently maintained high production levels due to their favorable coastal environments, extensive farming areas, and advancements in shrimp farming technologies. Additionally, Kien Giang exhibited the highest growth rate (10.95%) over the period, reflecting its rapid expansion in shrimp farming, while Tra Vinh (9.13%) and Soc Trang (8.95%) also demonstrated strong production increases. Despite having smaller production volumes, provinces such as Tien Giang and Ben Tre have shown remarkable growth rates of 8.82% and 7.28%, respectively, indicating their growing importance in the regional shrimp industry. In this study, we focus on Soc Trang, Bac Lieu, Ca Mau, and Kien Giang due to their dominant role in shrimp production, their contribution to both domestic supply and exports, and their potential for further development in sustainable shrimp farming practices.

The present study employs meticulously designed questionnaires for conducting face-to-face interviews with shrimp farmers. These questionnaires are designed to systematically gather information on three main aspects: (i) household demographic and economic characteristics; (ii) risk management strategies employed by shrimp farmers; and (iii) farmers' preferences regarding agricultural insurance utilizing the CM. Economic and demographic data are employed to identify factors influencing decision-making by shrimp farmers. The dataset on farm risk management strategies is collected to elucidate the strategies employed by farmers, assess their effectiveness, and contribute to proposing solutions for risk reduction. The final dataset is gathered to capture the

Table 3 Total shrimp production in the Mekong Delta. Unit: 1000 tons.
Source: [22]

Province	2005	2010	2015	2020	2023	Share 2023 (%)	Growth rate (%)
Long An	6.01	6.66	12.06	15.03	18.96	1.90	6.59
Tien Giang	8.00	12.83	20.60	27.68	36.62	3.66	8.82
Ben Tre	25.09	37.53	47.18	76.64	88.83	8.88	7.28
Tra Vinh	19.69	20.94	35.43	72.03	94.85	9.48	9.13
Soc Trang	42.84	60.83	90.66	155.53	200.53	20.05	8.95
Bac Lieu	63.62	69.10	104.11	147.48	206.98	20.70	6.77
Ca Mau	81.10	107.85	146.54	195.50	231.43	23.14	6.00
Kien Giang	18.46	34.77	52.21	98.11	119.91	11.99	10.95
Mekong Delta	265.76	353.20	510.56	789.75	1000.08	100.00%	7.64

preferences and willingness of farmers to pay for agricultural insurance, utilizing the CM model (Fig. 1).

To ensure that all shrimp farmers clearly understood the choice sets and how to make their selections, interviewers spent approximately 5–7 min explaining the three options—A, B, and C (status quo)—within each set. Additionally, the cheap talk script provided in Appendix 1 was clearly read and explained to respondents prior to the first choice task. Respondents were also provided with color-printed cards illustrating the choice sets to facilitate visualization and comparison during the decision-making process. To minimize bias, the choice sets were carefully designed using realistic scenarios and familiar terminology. The inclusion of a status quo option aimed to reflect actual decision-making constraints and to allow for opt-out behavior. Additionally, to ensure the reliability of farmers' responses regarding their willingness to purchase insurance packages or the options they selected, a 10-point Likert scale was used to measure their certainty after completing all choice sets. Only those respondents who reported a certainty level between 7 and 10 were included in the dataset for analysis.

Socio-demographics of shrimp farmers

Understanding the demographic characteristics of shrimp farmers is crucial for assessing their decision-making processes, access to resources, and potential adoption of new policies or technologies. Table 4 shows that shrimp farming in the Mekong Delta is predominantly male-dominated, with the highest male participation in Soc Trang (94%). Farmers have an aging demographic, with Bac Lieu having the oldest average age (55.71 years), while experience varies significantly, being highest in Ca Mau (18.26 years) and lowest in Soc Trang (9.97 years). Education levels remain low across all provinces, averaging between 6.76 and 7.93 years. Household sizes are relatively uniform, around

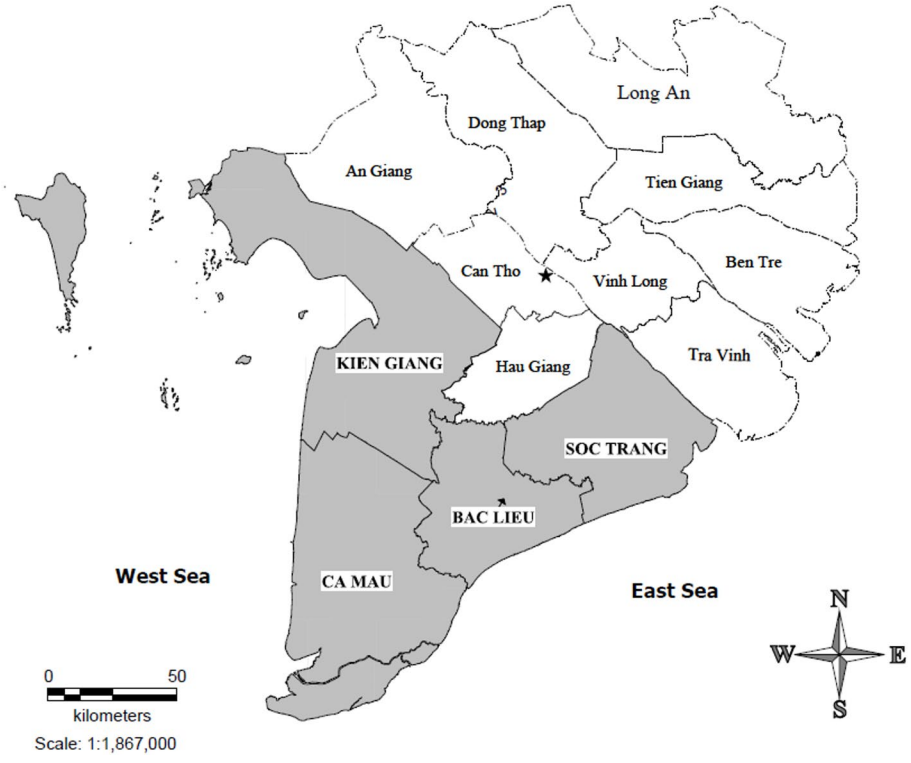


Fig. 1 The map of Mekong Delta and study sites

Table 4 Socio-demographic characteristics of shrimp farmers.
Source: Author's estimates based on survey data from 2023, n = 500

Indicators	Ca Mau		Soc Trang		Kien Giang		Bac Lieu	
	Mean	S.D	Mean	S.D	Mean	S.D	Mean	S.D
Gender (1 = male)	0.83	0.37	0.94	0.24	0.82	0.38	0.82	0.38
Age (years)	52.41	10.70	50.04	10.60	49.73	11.70	55.71	10.93
Family size (person)	4.35	1.51	3.86	1.07	4.34	1.25	4.23	1.50
Education (years)	7.35	3.21	7.09	3.40	7.93	3.68	6.76	3.58
Experience (years)	18.26	6.31	9.97	4.49	11.01	4.76	18.11	8.41
Cooperative (1 = yes)	0.18	0.39	0.19	0.39	0.41	0.49	0.40	0.49
Tiger shrimp (1 = yes)	0.73	0.44	0.00	0.00	1.00	0.00	0.80	0.39
White leg shrimp (1 = yes)	0.24	0.43	1.00	0.00	0.00	0.00	0.19	0.39
Extensive (1 = yes)	0.73	0.44	0.00	0.00	0.95	0.21	0.77	0.42
Intensive (1 = yes)	0.23	0.42	1.00	0.00	0.16	0.13	0.18	0.39
Semi-intensive (1 = yes)	0.03	0.16	0.00	0.00	0.03	0.18	0.04	0.19
Standard (1 = yes)	0.03	0.16	0.00	0.00	0.00	0.00	0.03	0.16
Training (1 = yes)	0.24	0.42	0.13	0.34	0.10	0.30	0.21	0.41
Credit access (1 = yes)	0.18	0.38	0.26	0.44	0.13	0.33	0.13	0.34
Pond area (ha)	0.97	0.97	0.31	0.16	1.57	0.75	0.85	10.82
Number of ponds	1.51	1.96	1.96	1.23	1.33	0.64	2.81	2.75
Water outlet	7.32	4.59	2.60	0.70	3.74	4.45	4.55	4.40
Water treatment	0.93	0.26	0.81	0.39	0.77	0.42	0.65	0.48

Data available upon reasonable request

four persons per household. Cooperative participation is more common in Kien Giang (41%) and Bac Lieu (40%) than in Soc Trang (19%) and Ca Mau (18%).

There is a clear regional distinction in shrimp species and farming methods: Soc Trang focuses exclusively on intensive white leg shrimp farming (100%), while Kien Giang (95%), Ca Mau (73%), and Bac Lieu (77%) favor extensive tiger shrimp systems. Access to training and credit remains limited, with training participation highest in Ca Mau (24%) and lowest in Kien Giang (10%), while Soc Trang has the highest credit access (26%). Farm infrastructure varies significantly, with Kien Giang having the largest pond areas (1.57 ha) and Ca Mau the highest number of water outlets (7.32), essential for effective water management in extensive farming. Water treatment usage is most prevalent in Ca Mau (93%) and lowest in Bac Lieu (65%), reflecting possible environmental concerns. Overall, regional disparities in farming systems, infrastructure, and resource access highlight the need for targeted interventions to enhance sustainability and profitability in shrimp production.

3.3 Data analysis

3.3.1 Multinomial logit model

Following McFadden [43], the choices made by respondents—specifically the farmers in this study—represent their perceived indirect utility for different attributes across various scenarios. The indirect utility function (U_{ij}) is expressed as follows:

$$U_{ij} = V_{ij} + e_{ij} = \beta X'_{ij} + \delta Z'_{ij} + e_{ij} \quad (1)$$

In this formulation, V_{ij} represents the deterministic component of the latent utility for respondent i^{th} associated with alternative j^{th} ($j = 1, \ldots, C$) within a given choice set. The parameter β is to be estimated, while e_{ij} accounts for the error component. Additionally, X'_{ij} and Z'_{ij} capture the attributes of agricultural insurance and the socio-economic

characteristics of respondent i^{th}. Consequently, the probabilistic response function for alternative *j* is expressed as follows:

$$\pi(j) = \exp(\beta X'_{ij} + \delta Z'_{ij}) / \sum_{J \epsilon C} \exp(\beta X'_{ij} + \delta Z'_{ij}) \tag{2}$$

Assuming that the distribution of e_{ij} is independently and identically distributed (*iid*) and follows an extreme value Type I distribution implies that the multinomial logit model (MNL) adheres to the independence of irrelevant alternatives (IIA) property. This property states that the probability ratio of choosing between any two options in a choice set remains unchanged regardless of the addition or removal of other alternatives. The IIA assumption can be evaluated using the Hausman and McFadden test. If this assumption is violated, alternative models such as the conditional logit model, random parameter logit model, or latent class model may be more appropriate. In this study, the latent class model is preferred as it allows for a deeper understanding of consumer behavior and market segmentation among shrimp farmers, offering valuable insights beyond what standard multinomial logit models can provide [32, 67].

Using Eqs. (1) and (2), the implicit price or marginal willingness to pay (MWTP) for each attribute of agricultural insurance can be estimated based on the following expressions for shrimp farmers.

$$MWTP = -\frac{\partial v_{ij} / \partial \beta_i}{\partial v_{ij} / \partial \beta_{ma}} = -\frac{\beta_i}{\beta_{ma}} \tag{3}$$

where β_i represents the coefficient of the attribute of interest, and β_{ma} denotes the coefficient of the monetary attribute.

3.3.2 Latent class choice model

The latent class model, originally developed by Swait [56], is widely used to analyze choice experiment data, particularly when the assumption of the independence of irrelevant alternatives (IIA) is violated. Also known as a finite mixture model, this approach is advantageous as it identifies and accounts for heterogeneous preferences among respondents by segmenting them into distinct groups with relatively similar choices. Research highlights the importance of incorporating latent individual characteristics in discrete choice analysis to better understand decision-making processes [5, 32, 44, 45]. Studies further suggest that preference heterogeneity is particularly prevalent in market analysis, especially in developing countries [16, 32, 67]. The latent class model assumes that individuals can be categorized into two or more distinct segments based on their attitudinal and socio-demographic characteristics, allowing for a more precise examination of consumer behavior.

According to and Swait [56], Louviere et al. [40], Boxall and Adamowicz [9], the latent class model represents the composite utility function as follows:

$$U_{ij/s} = \beta_s X'_{ji} + e_{ij/s} \tag{4}$$

Equation (4) represents the utility of the i^{th} respondent within a specific class or segment *s* when selecting alternative *j* in a given choice set *C*. The likelihood that a respondent opts for alternative *j* within segment *s* in the choice set can be expressed as:

$$P_{ij/s} = \exp(\beta_s X'_{ji}) / \sum_{k \epsilon C} \exp(\beta_s X'_{ki}) \tag{5}$$

Let P_{is} represent the probability that a consumer is assigned to one of the predefined latent segments. Based on the methodology introduced by and Swait [56], Ben-Akiva et al. [4], the probability of consumer *i* being classified into segment *s* is determined using the following expression.

$$P_{js} = \exp(\delta_s Z'_i) / \sum_{J \epsilon C} \exp(\delta_k Z'_i) \tag{6}$$

Here, Z'_i represents the socio-demographic, attitudinal, and perceptual characteristics of the i^{th} respondent, while δ_k denotes the parameters to be estimated. The latent class model, which incorporates both choice behavior and segment membership, can be formulated by jointly estimating the probabilities from Eqs. (5) and (6). Let P_{ijs} represent the joint probability that respondent *i* belongs to segment *s* and selects alternative *j*. This relationship can be expressed as follows:

$$P_{ijs} = (P_{ij/s})(P_{js}) = \left[\exp(\beta_s X'_{ji}) / \sum_{k \epsilon C} \exp(\beta_s X'_{ki})\right] \left[\exp(\delta_s Z'_i) / \sum_{J \epsilon C} \exp(\delta_k Z'_i)\right] \tag{7}$$

It is important to note that when the number of segments becomes comparable to the sample size, the use of a random parameter mixed logit model is recommended [21]. Additionally, if the constraints $\delta_s = 0$ and $\beta_s = \beta$ are applied, the model described in Eq. (7) simplifies to a standard multinomial logit model, implying that respondent preferences are homogeneous [32].

Several indicators have been proposed to determine the optimal number of segments *S* ($S \leq N$) [3, 40, 67]. This study utilizes three key criteria: the minimum Bayesian Information Criterion[1] (BIC), the minimum Bozdogan Akaike Information Criterion[2] (AIC3) and the maximum Akaike Likelihood Ratio Index[3] ($\overline{\rho}^2$).

4 Results and discussions

Before conducting the latent class choice model analysis, the study tested for multicollinearity among the variables. The results showed that no multicollinearity was present. Initially, the multinomial logit model was used as a benchmark to test the assumption of homogeneity, specifically the Independence of Irrelevant Alternatives (IIA) property. However, the Hausman and McFadden test indicated a violation of the IIA assumption, leading to its rejection. This suggests that consumer choices are heterogeneous, and therefore, the estimates from the multinomial logit model are likely biased. As a result, the latent class model, conditional logit model (CLM) and mixed logit model (MXL) were employed to better capture this heterogeneity in consumer preferences.

During the choice model estimation process, attempts were made to fit 3-class, 4-class, and 5-class latent class models to better capture preference heterogeneity among shrimp farmers. However, these models failed to converge due to computational limitations,

[1] $BIC = -LL + [((SK_\beta + (S-1)K_\delta)/2)\ln(N)]$.

[2] $AIC3 = -2LL + 3(SK_\beta + (S-1)K_\delta)$.

[3] $\overline{\rho}^2 = 1 - [(-2LL + (SK_\beta + (S-1)K_\delta))/2LL(0)]$.

where K_β and K_δ are the number of parameters in β and δ, respectively.

which we primarily attribute to the high frequency of status quo choices in the dataset. Importantly, this pattern should be interpreted in the broader context of respondents' real-world experiences and perceptions, rather than as a flaw in the experimental design. Notably, empirical findings reveal that 133 farmers—despite having a clear understanding of agricultural insurance—deliberately chose not to purchase due to a lack of trust in the system. In-depth discussions with farmers using open-ended questions also revealed that farmers' reluctance primarily stemmed from past negative experiences and a lack of trust, often rooted in perceived failures of previous pilot insurance programs. These individuals were not unfamiliar with the principles or functioning of insurance; rather, their repeated selection of the status quo reflects a rational and informed rejection, motivated by skepticism about the effectiveness and fairness of the system. The relatively high proportion of respondents selecting the status quo also suggests a meaningful level of engagement and indicates that responses were grounded in real-world considerations.

This finding aligns with evidence from previous studies, which highlight the erosion of farmer confidence following unsuccessful pilot phases of agricultural insurance [34, 35, 52]. Thus, the observed behavior should be understood not as confusion or disengagement with the survey, but as a considered response shaped by accumulated practical experience. Given these results, the analysis focused on evaluating the 1-Class Model and 2-Class Model using several statistical criteria, including Log Likelihood, BIC, AIC3, and McFadden's Pseudo R^2 ($\overline{\rho^2}$). These metrics assess the balance between model fit and complexity, ensuring that the selected model effectively captures preference heterogeneity without overfitting.

Based on the model evaluation criteria in Table 5, the 2-Class Model has a lower BIC and AIC3 compared to the 1-Class Model. This suggests that the 2-Class Model provides a better fit for the data while balancing complexity. Additionally, McFadden's Pseudo R^2 ($\overline{\rho^2}$) is higher for the 2-Class Model, indicating better explanatory power. Therefore, the 2-Class Model is recommended as the preferred model for capturing heterogeneity in farmers' insurance preferences.

Understanding the factors influencing shrimp farmers' willingness to pay for index insurance requires examining the heterogeneity in their preferences and decision-making. By applying a latent class choice model, we can identify distinct farmer segments with varying levels of risk perception, price sensitivity, and preference for different insurance attributes. This segmentation helps explain why some farmers are more likely to adopt index insurance while others remain hesitant. The application of the latent class model not only confirms the presence of such heterogeneity in a new empirical context but also serves to inform more targeted policy interventions, particularly in Vietnam, where agricultural insurance markets remain underdeveloped and adoption rates are low. Table 6 shows the estimated coefficients from the latent class choice model,

Table 5 Criteria for determining optimal number of latent segments

Criteria	1-class model	2-class model
Log likelihood (LL)	− 2104.04	− 2043.14
Number of parameters (K)	7	29
BIC	2262.22	2131.43
AIC3	4254.29	4229.09
McFadden's pseudo R^2 ($\overline{\rho^2}$)	1.9806	1.9979

Table 6 Estimated coefficients from latent class choice model.
Source: Author's estimates based on survey data from 2023, n = 500

Variables	Segment 1 Training-responsive, price-sensitive farmers with low education		Segment 2 Company-trusting, moderately price-sensitive farmers with higher education	
	Coef	S.E	Coef	S.E
Utility function coefficients				
ASC	−2.534***	0.427	−0.948***	0.163
DAY40	0.646*	0.336	0.191*	0.113
DAY50	0.775**	0.340	−0.178	0.117
SEASON	0.881***	0.286	0.185**	0.089
WEATHER	−0.095	0.238	0.033	0.086
COMPANY	−0.559*	0.288	0.325***	0.092
PRICE	−0.474**	0.186	−0.218***	0.069
Segment function coefficients				
CONSTANT	−16.558	20,328.240	–	
FAMILY SIZE	−3.775**	1.720	–	
SHRIMP LABOR	0.687***	0.234	–	
EDUCATION	−1.248**	0.579	–	
COOPERATIVE	0.008	0.074	–	
TIGER SHRIMP	−2.708*	1.466	–	
WHITE LEG SHRIMP	−21.190	13,407.970	–	
EXTENSIVE FARMING	20.693	20,328.240	–	
INTENSIVE FARMING	39.750	24,351.820	–	
STANDARD	0.407	1.509	–	
TRAINING	4.082*	2.457	–	
CREDIT	−73.902	0.142×10^8	–	
Class probabilities	37.90%		62.10%	
Model parameters				
Log likelihood function	−2031.378			
McFadden Pseudo R^2	0.260			
Observations	2500			

Data available upon reasonable request

*, ** and *** indicate the significant levels of 10%, 5% and 1%, respectively

emphasizing the key factors that distinguish the farmer groups and their likelihood of purchasing index insurance.

To better understand shrimp farmers' willingness to pay for index insurance, the latent class choice model was estimated, identifying two distinct segments with differing preferences and decision-making behaviors. The results suggest that segment 1 consists of farmers with lower levels of education, smaller household sizes, and a heavy reliance on labor for shrimp farming. They are highly responsive to training programs, suggesting strong potential for behavioral change when appropriate support is available. These farmers are open to innovative insurance designs, particularly those that offer early payouts (40–50 days after stocking) and align with seasonal farming cycles. However, they are highly price-sensitive and tend to be skeptical of company involvement in insurance provision. Therefore, this segment is labeled "Training-responsive, price-sensitive farmers with low education". In contrast, Segment 2 includes farmers who are more educated, less reliant on shrimp labor, and less influenced by training. They prefer insurance options involving company participation, indicating greater trust in formal institutions. While still price-sensitive, they are more accepting of the status quo and show moderate

Table 7 Estimated willingness to pay for insurance attributes.
Source: Author's estimates based on survey data from 2023, n = 500. Data available upon reasonable request

Attribute	Latent class		Conditonal logit WTP (%)	Mixed logit WTP (%)
	Segment 1 WTP (%)	Segment 2 WTP (%)		
Insurance coverage start Time (40 days)	1.36*	0.88*	1.21***	− 0.13
Insurance coverage start Time (50 days)	1.64**	− 0.82	0.08	− 1.83***
Insurance coverage duration (seasonal)	1.86***	0.85**	1.22***	0.78***
Loss assessment method (Weather-based)	− 0.20	0.15	0.05	− 5.62***
Claim procedures (Company-assisted)	− 1.18*	1.49***	0.67**	− 0.32***

1USD = 25,600 VND

interest in early payouts and seasonal coverage. This segment is labeled "Company-trusting, moderately price-sensitive farmers with higher education".

The model's pseudo R^2 of 0.260 indicates a reasonable fit, providing valuable insights into the heterogeneity of shrimp farmers' preferences. To enhance the robustness of our findings and address the observed dominance of the status quo option, we supplemented the LCCM with two additional models: the CLM, with results presented in Appendix 2, and the MXL, with results shown in Appendix 3. While the LCCM captures preference heterogeneity through distinct segments, the CLM assumes homogeneous preferences across all respondents, and the MXL accounts for continuous heterogeneity in preferences. Table 7 presents the detailed estimated WTP values for each insurance attribute across the LCCM, CLM, and MXL models.

*, ** and *** indicate the significant levels of 10%, 5% and 1%, respectively

The estimated WTP values reveal significant differences between the two farmer segments in their preferences for index insurance attributes. Segment 1 farmers show a strong preference for extended insurance coverage, with a WTP of 1.36% of total revenue for coverage starting at 40 days and 1.64% of total revenue for coverage at 50 days, suggesting they perceive greater risks and value longer protection. In contrast, Segment 2 is willing to pay 0.88% of total revenue for 40-day coverage but has a negative WTP (− 0.82) for 50-day coverage, indicating they do not favor later-stage insurance. Seasonal insurance is preferred by both segments, though Segment 1 values it higher (1.86% of total revenue) compared to Segment 2 (0.85% of total revenue Regarding loss assessment, Segment 1 has a slightly negative WTP (− 0.20% of total revenue) for weather-based assessment, suggesting concerns about reliability, while Segment 2 has a positive WTP (0.15% of total revenue), showing more trust in this method. The most striking difference is in claim procedures: Segment 1 strongly dislikes company-assisted claims (− 1.18% of total revenue), preferring self-processed claims, while Segment 2 has a WTP of 1.49% of total revenue for company-assisted claims, indicating they value administrative support.

Table 7 also shows that the estimation results from the LCCM, CLM, and MXL highlight consistent patterns and confirm preference heterogeneity among shrimp farmers. The CLM, assuming homogenous preferences, yields average WTP values that typically fall between the two LCCM segments—for example, a WTP of 1.21% for 40-day coverage aligns more with Segment 1. Seasonal insurance is positively valued across all models, indicating broad farmer support. However, differences emerge for other attributes: CLM shows a positive WTP (0.67%) for company-assisted claims, contrary to Segment

1's rejection of this option in LCCM. MXL further reveals significant heterogeneity, with extreme values such as a large negative WTP (–5.62%) for weather-based loss assessment. These results suggest that farmers are generally unwilling to pay for weather-based agricultural insurance. This reluctance may stem from a lack of trust in the monitoring systems and past failures of pilot programs. Farmers may feel the need to be actively involved in the damage assessment process. However, there is substantial variation across households—specifically, the statistically significant coefficient for NsWEATHER in the "Distributions of Random Parameters" indicates that farmers exhibit diverse preferences regarding this damage assessment attribute. Similarly, for the attribute "50 days after stocking", farmers' willingness to pay also tends to be lower compared to the 60-day mark. This may be because, at 50 days, both the investment value and the economic value of the shrimp are still relatively low. Additionally, ponds may not yet be heavily affected by pollution, leading farmers to perceive a lower risk of potential losses at this stage. However, the results also indicate heterogeneity in farmers' preferences for this attribute, as evidenced by the statistically significant coefficient of NsDAY50.

Despite methodological differences, both LCCM and MXL consistently capture diverging views on coverage duration and claim procedures, emphasizing the need for flexible, tailored insurance designs that address diverse farmer needs and perceptions.

By combining the class membership results with the estimated willingness to pay for each attribute, the findings highlight the need for insurance providers to tailor products to the distinct characteristics of each farmer segment to improve adoption rates. For Segment 1 (low-education, training-responsive farmers), insurers should focus on offering early payout and seasonal coverage options, which align with this group's preferences. Given their skepticism toward company involvement, it is important to build trust through ongoing training and extension services, which this group responds well to. Additionally, incorporating more flexible and transparent claim processes, such as self-assessment or participatory damage verification, may help overcome distrust and encourage participation. These findings align with studies highlighting the importance of tailoring insurance products to address the specific needs of different farmer segments. For instance, a study on Vietnamese shrimp farmers found that farmers' risk management strategies and willingness to pay are influenced by their experiences and perceptions of insurance reliability [2]. Regarding to Segment 2 (higher-education, company-trusting farmers), insurance providers can leverage this group's greater acceptance of company involvement by offering products with clearly defined institutional roles and streamlined processes. While they are still price-sensitive, their moderate willingness to pay suggests potential for adopting more structured or bundled insurance packages, especially when paired with transparent pricing and reliable service. Since this group is less influenced by training, outreach efforts should focus on highlighting the credibility and efficiency of insurance providers, rather than capacity-building. Emphasizing the role of trusted organizations may further enhance uptake within this segment. This segment's preferences are consistent with findings from other studies, which suggest that ease of access and convenience are significant factors influencing insurance uptake among farmers. For example, research on small-scale Vietnamese shrimp farmers indicates that preferences for good aquaculture practices and proactive development policies are influenced by the perceived benefits and convenience of adoption [42, 53]. The identification of these segments through latent class analysis contributes to a nuanced

understanding of farmer behaviors, which is crucial for developing effective risk management strategies. Recognizing that a one-size-fits-all approach is ineffective, policymakers and insurers can leverage these insights to craft policies that resonate with the diverse needs of the farming community, thereby enhancing the sustainability and effectiveness of agricultural insurance schemes [49].

5 Conclusions

The analysis highlights clear differences in insurance preferences between the two segments, emphasizing the need for tailored approaches. Segment 1—training-responsive, price-sensitive farmers with low education—prefers seasonal and extended coverage but is skeptical of company involvement and weather-based assessments. Their strong responses to training and high price sensitivity suggest a need for capacity-building and financial support. In contrast, Segment 2—company-trusting, moderately price-sensitive farmers with higher education—prefers company-assisted claims and weather-based assessments, reflecting greater trust in formal systems. For this group, strategies should focus on credibility, clear procedures, and efficient service delivery. The estimation results from the LCCM and MXL highlight consistent patterns and confirm preference heterogeneity among shrimp farmers. These findings suggest that a one-size-fits-all approach may not be effective in promoting index insurance adoption among shrimp farmers. Instead, insurance providers should develop customized policy options that align with the distinct needs of each segment. Offering flexible claim procedures, multiple coverage durations, and transparent loss assessment methods can enhance the appeal of index insurance and encourage broader participation. By addressing these varied preferences, policymakers and insurers can design more effective and sustainable risk management solutions for shrimp farmers, ultimately improving their resilience to production uncertainties.

While this study offers valuable insights into shrimp farmers' willingness to pay for index insurance, several limitations should be acknowledged. First, the analysis is based on stated preference data derived from a discrete choice experiment, which may not fully reflect actual purchasing behavior in real-world contexts. Second, although the study focuses on a set of key insurance attributes, there is an inherent trade-off between including a comprehensive range of attributes and maintaining the cognitive simplicity and statistical efficiency of the experimental design. Due to constraints in constructing an orthogonal and manageable design, certain potentially important factors—such as government subsidies, peer influence, coverage caps, or prior experience with insurance—were not incorporated. Future research should explore these additional dimensions to provide a more comprehensive understanding of farmers' insurance adoption behavior and to inform more nuanced policy design.

Appendix 1: An example choice set for index insurance

Before you begin the choice tasks regarding agricultural insurance packages, we would like you to consider the following: In previous surveys, some farmers tended to choose options that sounded "ideal" or "desirable" rather than the ones they would realistically choose if they actually had to pay for them. In reality, farmers make careful decisions based on their farming, perceived risks, and the actual value of the insurance. So we kindly ask you to answer this survey as if you were really deciding whether to pay for

each insurance option using your own money. Please consider each choice carefully, just as you would if this were a real-life decision.

Attribute	Insurance package A	Insurance package B	No agricultural insurance
Insurance coverage start time	40 days after stocking	50 days after stocking	
Insurance coverage duration	Annual insurance package	Seasonal insurance package	
Loss assessment method	Weather-based assessment	On-site farm assessment	
Claim procedures	Company-assisted process	Self-processed claims	
Insurance premium rate	1.5% of total revenue	2% of total revenue	
I will choose: (Select only one option)	☐ Insurance package A	☐ Insurance package B	☐ I will not purchase

Appendix 2: Estimated coefficients from conditional logit model

Variables	Coefficients	Standard error	z	Prob|z| >Z
ASC	−1.433***	0.120	−11.920	0.000
DAY40	0.301***	0.091	3.320	0.001
DAY50	0.019	0.091	0.210	0.837
SEASON	0.303***	0.073	4.140	0.000
WEATHER	0.013	0.072	0.180	0.854
COMPANY	0.166**	0.072	2.310	0.021
PRICE	−0.248***	0.055	−4.510	0.000

Appendix 3: Estimated coefficients from mixed logit model

Variables	Coefficients	Standard error	z	Prob|z| >Z
Random parameters in utility functions				
DAY50	−1.779***	0.609	−2.920	0.004
WEATHER	−5.455***	1.914	−2.850	0.004
Nonrandom parameters in utility functions				
DAY40	−0.127	0.116	−1.090	0.274
SEASON	0.757***	0.160	4.720	0.000
COMPANY	−0.312***	0.111	−2.800	0.005
PRICE	−0.971***	0.079	−12.240	0.000
Distributions of random parameters				
NsDAY50	2.508***	0.785	3.190	0.001
NsWEATHER	7.487***	2.196	3.410	0.001

Acknowledgements
This research is funded by Vietnam National Foundation for Science and Technology Development (NAFOSTED) under grant number 502.01-2021.09.

Author contributions
V.H.T: Conceptualization, methodology, data analysis, writing—original draft preparation, and final manuscript revision.N.T.T: Funding acquisition, conceptualization, methodology, data collection, writing—review and editing, and manuscript supervision. H.N: Methodology, data analysis, and writing—review and editing.Y.T: Methodology, data analysis, and writing—review and editing.

Data availability
The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
The research was reviewed and approved by the Research Ethics Committee for Social Sciences and Humanities at Can Tho University under application number: CTU-RECSH24007. Participants were provided with a consent form containing

the following information: a brief introduction to the study, the purpose of the study, confidentiality, voluntary participation and right to withdraw, contact information, and the consent statement.

Consent to publish
Not applicable.

Competing interests
The authors declare no competing interests.

Clinical trial number
Not applicable.

Received: 6 April 2025 / Accepted: 10 September 2025
Published online: 23 October 2025

References

1. Adeyinka AA, Kath J, Nguyen-Huy T, Mushtaq S, Souvignet M, Range M, et al. Global disparities in agricultural climate index-based insurance research. Clim Risk Manag. 2022;35:100394.
2. Akter A, Alam MT, Mondol M, Ullah M. Shrimp cultivators' willingness to pay for index based aquaculture insurance in the south-western region of Bangladesh. J Econ. 2021;3(1):109–26.
3. Andrews RL, Currim IS. A comparison of segment retention criteria for finite mixture logit models. J Mark Res. 2003;40(2):235–43.
4. Ben-Akiva M, Walker J, Bernardino AT, Gopinath DA, Morikawa T, Polydoropoulou A. Integration of choice and latent variable models. In: Paper presented at the International Association of Travel Behavior Research Conference (IATBR), Austin, Texas, 21–25 September 1997; 1997.
5. Ben-Akiva M, Walker J, Bernardino AT, Gopinath DA, Morikawa T, Polydoropoulou A. Integration of choice and latent variable models. In: Perpetual motion: travel behaviour research opportunities and application challenges; 2002. p. 431–70.
6. Bernstein L, Bosch P, Canziani O, Chen Z, Christ R, Riahi K. IPCC, 2007: climate change 2007: synthesis report: IPCC; 2008.
7. Binh NT, Tam NTT, Can ND. Factors Influencing Changes in Farming Systems in Salinity-Affected Areas of My Xuyen District, Soc Trang Province. In the proceedings of the workshop "Sustainable Development of Rice–Shrimp Farming Systems in the Coastal Areas of the Mekong Delta"; 2009. p. 37–48.
8. Birol E, Karousakis K, Koundouri P. Using a choice experiment to account for preference heterogeneity in wetland attributes: the case of Cheimaditida wetland in Greece. Ecol Econ. 2006;60(1):145–56.
9. Boxall PC, Adamowicz WL. Understanding heterogeneous preferences in random utility models: a latent class approach. Environ Resource Econ. 2002;23(4):421–46.
10. Brouwer R, Akter S. Informing micro insurance contract design to mitigate climate change catastrophe risks using choice experiments. Environ Hazards. 2010;9(1):74–88.
11. Carew-Reid J. Rapid assessment of the extent and impact of sea level rise in Viet Nam. International Centre for Environment Management (ICEM), Brisbane, 82; 2008.
12. Clarke DJ, Clarke D, Mahul O, Rao KN, Verma N. Weather based crop insurance in India. World Bank Policy Research Working Paper(5985); 2012.
13. Clayton H. Rice–shrimp farming in the Mekong Delta: biophysical and socioeconomic issues. Australian Centre for International Agricultural Research; 2003.
14. Chambers RG. Insurability and moral hazard in agricultural insurance markets. Am J Agric Econ. 1989;71(3):604–16.
15. Díaz Nieto J, Fisher M, Cook S, Läderach P, Lundy M. Weather indices for designing micro-insurance products for smallholder farmers in the tropics. PLoS ONE. 2012;7(6):e38281.
16. Dillon WR. Latent structure and other mixture models in marketing: an integrative survey and overview. Adv Methods Market Res. 1994.
17. Diyyala R, Palanichamy NV, Kalpana M, Murugananthi D, Geethalakshmi V, Rajavel M. Does insurance knowledge and loss experience influence the adoption of Pradhan Mantri Fasal Bima Yojana? Insights from cotton farmers in Tamil Nadu, India. J Exp Agric Int. 2024. https://doi.org/10.9734/jeai/2024/v46i102937.
18. Ellis RP, McGuire TG. Supply-side and demand-side cost sharing in health care. J Econ Perspect. 1993;7(4):135–51.
19. FAO. Aquaculture insurance for small-scale producers. Rome: FAO Innovation for Blue Transformation; 2024.
20. Fischer A, Hanley N. Analysing decision behaviour in stated preference surveys: a consumer psychological approach. Ecol Econ. 2007;61(2–3):303–14.
21. Greene WH, Hensher DA. A latent class model for discrete choice analysis: contrasts with mixed logit. Transp Res Part B Methodol. 2003;37(8):681–98.
22. GSO. Statistical Yearbook of Vietnam 2023. Ha Noi, Vietnam: Statistical Publishing House; 2024.
23. Harwood JL. Managing risk in farming: concepts, research, and analysis: US Department of Agriculture, ERS; 1999.
24. Huang Z-Y, Alec Z, Sun J-M, Guo Y-Z. Potato farmers' preference for agricultural insurance in China: an investigation using the choice experimental method. J Integr Agric. 2020;19(4):1137–48.
25. Huirne RB, Meuwissen MP, Hardaker JB, Anderson JR. Risk and risk management in agriculture: an overview and empirical results. Int J Risk Assess Manag. 2000;1(1–2):125–36.
26. IPCC. Climate Change 2014: Mitigation of climate change. Contribution of working group III to the fifth assessment report of the intergovernmental panel on climate change, 1454; 2014. p. 147.
27. IPCC. Climate Change 2022: Mitigation of Climate Change. Intergovernmental Panel on Climate Change; 2022.
28. Jensen N, Barrett C. Agricultural index insurance for development. Appl Econ Perspect Policy. 2017;39(2):199–219.
29. Jensen ND, Barrett CB, Mude AG. Index insurance quality and basis risk: evidence from northern Kenya. Am J Agric Econ. 2016;98(5):1450–69.
30. Just RE, Calvin L, Quiggin J. Adverse selection in crop insurance: actuarial and asymmetric information incentives. Am J Agric Econ. 1999;81(4):834–49.

31. Kiet NT, Phat NT. Response of farmers to risks in agricultural agricultural production in Can Tho city. Can Tho Univ J Sci. 2019;55:135–47.
32. Kontoleon A, Yabe M. Market segmentation analysis of preferences for GM derived animal foods in the UK. J Agric Food Ind Organ. 2006;4(1):1150.
33. Khoi PD, Dong KTP, Khoa DD, Hoa NTN. Factors affecting to farmer's decision making to participate to the agricultural insurance programs on rice crops in Vietnam's Mekong Delta. Van Hien Univ J Sci. 2022;8(2):1–13.
34. Khoi PD, Hiep QV. Determinants of households' decision to purchase insurance for shrimp farming in Bac Lieu Province. Can Tho Univ J Sci. 2014;35(2014):97–104.
35. Khoi PD, Khai HV. The demand for insuance of shrimp farmers in Bac Lieu; 2017.
36. Khoi PD, Thao PLN. Impact of the pilot shrimp insurance program on the income of shrimp farmers in Bac Lieu. J Econ Dev. 2016;35 (2014):97–104.
37. Lancaster KJ. A new approach to consumer theory. J Polit Econ. 1966;74(2):132–57.
38. Le VD, Pham LT. Attitudes towards risk and optimal use of inputs in Maize production in the Mekong Delta, Vietnam. Paper presented at the The 1stASEAN University Symposium for Sustainable Food and Hybrid Systems, Faculty of Economics, Kasetsart Universit, Bangkok, Thailand, April 18th–9th, 2024; 2024.
39. Liesivaara P, Myyrä S. Willingness to pay for agricultural crop insurance in the northern EU. Agric Financ Rev. 2014;74(4):539–54.
40. Louviere JJ, Hensher DA, Swait JD. Stated choice methods: analysis and applications. Cambridge University Press; 2000.
41. Mahul O, Stutley CJ. Government support to agricultural insurance: challenges and options for developing countries. World Bank Publications; 2010.
42. Mato-Amboage R, Touza J, Soliño M. Understanding farmers' preferences towards insurance schemes that promote biosecurity best management practices. Int J Disaster Risk Sci. 2022;13(5):705–15.
43. McFadden D. The measurement of urban travel demand. J Public Econ. 1974;3(4):303–28.
44. McFadden D. The choice theory approach to market research. Mark Sci. 1986;5(4):275–97.
45. McFadden D, Machina MJ, Baron J. Rationality for economists? Elicitation of preferences. . Springer; 1999. p. 73–110.
46. Miranda MJ, Farrin K. Index insurance for developing countries. Appl Econ Perspect Policy. 2012;34(3):391–427.
47. Mogas J, Riera P, Bennett J. A comparison of contingent valuation and choice modelling with second-order interactions. J Forest Econ. 2006;12(1):5–30.
48. MORNE. The climate change and sea level rise scenarios of Vietnam. Ha Noi: Environmental Resources and Maps Publishing House; 2016.
49. Myyrä S, Liesivaara P. One size policy does not fit all: latent farmer groups in crop insurance markets in Finland. Outlook Agric. 2015;44(4):297–302.
50. Nhan DK, Trung NH, Van Sanh N. The impact of weather variability on rice and aquaculture production in the Mekong Delta. In: Stewart MA, Coclanis PA, editors. Environmental change and agricultural sustainability in the Mekong Delta. Springer; 2011. p. 437–51.
51. Patil V, Veettil PC. Farmers' risk attitude, agricultural technology adoption and impacts in eastern India. Agric Food Secur. 2024;13(1):50.
52. Prabhakar S, Rao GS, Fukuda K, Hayashi S. Promoting risk insurance in the Asia–Pacific region: lessons from the ground for the future climate regime under UNFCCC. Climate change adaptation in practice: from strategy development to implementation; 2013. p. 303–23.
53. Phong TN, Thang VT, Hoai NT. What motivates farmers to accept good aquaculture practices in development policy? Results from choice experiment surveys with small-scale shrimp farmers in Vietnam. Econ Anal Policy. 2021;72:454–69.
54. Sibiko KW, Veettil PC, Qaim M. Small farmers' preferences for weather index insurance: insights from Kenya. Agric Food Secur. 2018;7:1–14.
55. Slovic P, Fischhoff B, Lichtenstein S. Why study risk perception? Risk Anal. 1982;2(2):83–93.
56. Swait J. A structural equation model of latent segmentation and product choice for cross-sectional revealed preference choice data. J Retailing Consumer Serv. 1994;1(2):77–89.
57. Tac NV, Khiem NT. Willingness to pay for insurance premium of rice farmers in Hau Giang province. J Econ Dev. 2019;269:72–81.
58. Tu VH, Kopp SW, Trang NT, Kontoleon A, Yabe M. UK consumers' preferences for ethical attributes of floating rice: implications for environmentally friendly agriculture in Vietnam. Sustainability. 2021;13(15):8354.
59. Tyagi NK, Joshi PK. Index-based insurance for mitigating flood risks in agriculture: status, challenges and way forward. Climate Smart Agriculture in South Asia: Technologies, Policies and Institutions; 2019. p. 183–204.
60. Thang NV, Mau ND, Thang VV, Long PT. Climate change and scenarios for climate change in the Mekong Delta. Paper presented at the Conference proceedings about "Policies for adaptation to climate change in the Mekong Delta, Vinh Long province; 2020.
61. Trang NT. Economic and environmental efficiency of intensive shrimp farming in the coastal transforming areas of the Mekong Delta. (Dotoral dissertation), Can Tho University, Can Tho; 2020.
62. Trang NT, Kopp SW, Tu VH, Yabe M. Urban Vietnamese consumers' preferences for attributes of sustainably produced rice. J Consum Market. 2023;40(3):286–304.
63. Trang NT, Tu VH, Son LT, Son NP. Is super-intensive shrimp farming more environmentally friendly? An application of material balance principle in the Mekong Delta. Environ Dev Sustain. 2023;25(3):2670–87.
64. Trang NT, Kopp WS, Tu VH. Sustainable development of local livelihoods in Vietnam: A demand-driven approach through "One Commune, One Product". Sustainable Development; 2025.
65. Walker T, Jodha N. How small farm households adapt to risk. In: Hazell P, editor. Crop insurance for agricultural development. Issues and experience. Maryland: The Johns Hopkins University Press; 1986.
66. Wassmann R, Hien NX, Hoanh CT, Tuong TP. Sea level rise affecting the Vietnamese Mekong Delta: water elevation in the flood season and implications for rice production. Clim Change. 2004;66(1):89–107.
67. Wedel M, Kamakura WA. Market segmentation: conceptual and methodological foundations, vol. 8. Springer; 2012.
68. Ye T, Wang M, Hu W, Liu Y, Shi P. High liabilities or heavy subsidies: farmers' preferences for crop insurance attributes in Hunan, China. China Agric Econ Rev. 2017;9(4):588–606.

69. Zheng H, Mu H, Zhao X. Evaluating the demand for aquaculture insurance: an investigation of fish farmers' willingness to pay in central coastal areas in China. Mar Policy. 2018;96:152–62.

Publisher's note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.