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Explaining and Predicting HDPE-Lined Shrimp Pond Expansion: Theory-Informed Modeling Versus XGBoost

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Abstract: Decisions to expand an established production technology differ from decisions to adopt it initially because further deployment requires additional capital, land, and management capacity. This study investigates the intention of experienced shrimp-farming households to expand high-density polyethylene-lined pond area in post-merger Can Tho City, Vietnam. Cross-sectional survey data from 356 current users were examined using partial least squares structural equation modeling, followed by extreme gradient boosting and Shapley additive explanations to assess out-of-sample prediction and model-based feature contributions. Perceived value showed the strongest positive association with expansion intention (standardized coefficient = 0.568). Expected economic benefits, social media influence, and perceived climate and disease threats were positively associated with perceived value, whereas perceived investment and operating cost burden was negatively associated with it. Contrary to the proposed hypothesis, technological readiness weakened the association between perceived value and expansion intention (interaction coefficient = −0.191). A theory-informed linear benchmark incorporating this interaction performed better than the tuned boosting model on the holdout sample (predictive explained variance of 0.283 versus 0.163). This finding suggests that model complexity did not improve predictive accuracy in the present dataset. By focusing on households with operational experience, the study identifies a boundary condition in translating favorable technology evaluations into expansion intentions. The analysis distinguishes explanatory associations from predictive patterns, although its cross-sectional, geographically concentrated sample does not support causal or nationwide claims.

Keywords: Expansion Intention; High-Density Polyethylene-Lined Ponds; Perceived Value; Technological Readiness; Explainable Machine Learning.

INTRODUCTION

The decision to expand HDPE-lined shrimp production is not simply a continuation of current practice but an additional investment made after farmers have gained operating experience. Expansion requires more pond area, working capital, and management capacity; positive experience with existing ponds therefore does not necessarily justify further deployment. Aquaculture produced 103 million tonnes of aquatic animals in 2024, accounting for 53% of global production (Food and Agriculture Organization of the United Nations, 2026). In Vietnam's Mekong Delta, shrimp-farming investment is made under substantial environmental and biological uncertainty. Do and Ho (2022) show that climate perceptions influence adaptation choices, while Le et al. (2024) identify climatic events, farm conditions, and management practices as relevant to disease occurrence. Expansion is therefore a risk–return decision rather than a purely technical choice. Evidence specific to pond lining remains limited. Do and Ho (2022) include plastic pond lining among adaptation practices, but reported productivity gains are associated with other measures. Financial constraints are also important. Xuan and Sandorf (2020) show that capital access and credit incentives affect willingness to invest in higher-technology shrimp production, while Ngoc et al. (2021) highlight expected yield and crop success in farmers' investment preferences. The central problem is therefore why experienced HDPE users choose to expand, or maintain, their current scale. This study defines expansion intention as the stated intention to increase the absolute area of operating HDPE-lined shrimp

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ponds. It focuses on current users who have completed at least one production cycle and examines prospective expansion rather than initial adoption or observed expansion behavior.

Existing Vietnamese evidence explains several neighboring decisions, but not the focal one. Joffre et al. (2019) examine how farmer networks and risk perceptions shape the adoption of shrimp-management practices. Do and Ho (2022) focus on climate-adaptation choices, whereas Ngoc et al. (2021) analyze willingness to invest in improved shrimp-production methods. Ulhaq et al. (2022) study intention to adopt monitoring-related ICT among intensive shrimp farmers. None of these outcomes is equivalent to the intention of an experienced HDPE user to increase the absolute area of lined ponds. The first gap is therefore decision-stage specific: evidence on initial adoption, technology acceptance, or management-practice adoption cannot be assumed to explain post-adoption expansion. The second gap concerns the mechanism linking competing considerations to expansion intention. The value-based adoption model treats perceived value as an overall assessment formed by weighing benefits against sacrifices (Kim et al., 2007). Agricultural evidence also shows that perceived value can be relevant to technology adoption (Jayashankar et al., 2018). What remains untested is whether experienced HDPE farmers integrate expected economic benefits, production threats, social-media information, and financial burden into a value judgment that subsequently relates to additional area investment. A third gap concerns the boundary between favorable evaluation and actionable expansion. Ulhaq et al. (2022) show that confidence in learning new technology matters in shrimp farmers' technology evaluations, suggesting that competence beliefs may constrain how value is translated into behavior. This study therefore tests task-specific technological readiness as a moderator of the perceived value-expansion intention relationship. It also separates explanation from prediction. Shmueli (2010) argues that explanatory fit and predictive performance answer different questions; the proposed PLS-SEM and XGBoost-SHAP design follows that distinction rather than treating one form of evidence as a substitute for the other.

For the journal's informatics scope, the computational question is whether a theory-specified interaction model generalizes as well as a flexible machine-learning alternative on unseen responses. Accordingly, the article evaluates predictive accuracy and model transparency rather than claiming a new algorithm or a deployed decision-support system. Recent applications of explainable analytics in agricultural decision support provide a useful methodological context (Shams et al., 2024; Yenkikar et al., 2025).

The study addresses three research questions: ***RQ1***. How are expected economic benefits, social media influence, perceived climate and disease threats, and investment and operating cost burden associated with perceived value among existing HDPE shrimp farmers? ***RQ2***. How is perceived value associated with expansion intention, what indirect associations does it transmit from its antecedents, and does technological readiness strengthen the value intention relationship? ***RQ3***. Does XGBoost improve prediction of expansion intention beyond appropriate benchmarks on observations excluded from model training, and what nonlinear or interaction patterns help explain its predictions?

The substantive contribution lies in distinguishing further deployment by experienced users from initial adoption and routine continuance. This focus changes the investment question. Farmers' experience with existing ponds can inform expected benefits, while additional area still exposes them to new costs and management demands. The model can therefore examine why a favorable assessment of HDPE may coexist with limited willingness to expand. The theoretical contribution is a context-specific extension of value-based reasoning. It places production threats and social media information alongside economic benefits and financial sacrifices, then identifies perceived operational readiness as a possible boundary condition on translating value into expansion intention. The contribution depends on whether these relationships receive empirical support and remain distinguishable in measurement. Applying an established model in another location alone would provide a weaker contribution. The analytical contribution is the planned comparison between theory-specified explanation and flexible prediction. PLS-SEM will estimate the proposed construct relationships, while out-of-sample assessment will be used to evaluate predictive performance rather than infer it from explanatory fit, consistent with Shmueli et al. (2019). XGBoost provides a flexible tree-boosting framework capable of representing nonlinearities and interactions (Chen & Guestrin, 2016). SHAP will then be used to attribute the trained model's predictions to its inputs following the additive explanation framework of Lundberg and Lee (2017). Any nonlinear pattern will be interpreted as a predictive regularity, not as causal evidence.

Section II reviews the relevant literature, sharpens the research gap and develops the hypotheses. Section III sets out the research methodology. The article then presents the empirical results, discuss their theoretical and practical implications, and conclude with the study's limitations and directions for further research.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Expansion As A Distinct Investment Decision

The expansion decision follows experience with a technology but remains prospective. A household that has completed a production cycle can evaluate HDPE using its own operating experience. Its intention to allocate additional pond area depends on what it expects from further deployment. Existing benefits can inform that expectation without guaranteeing that the next investment will perform equally well. Chavas and Nauges (2020)

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review agricultural technology adoption through uncertainty and learning, providing a basis for treating farmers' evaluations as responsive to experience rather than fixed at the point of adoption.

Acceptance and continuance also require conceptual separation. Bhattacherjee (2001) shows that continuing to use a technology involves beliefs and evaluations that differ from initial acceptance. This distinction is relevant here without making the expectation-confirmation model the article's governing framework. Expansion adds another decision: committing resources to more HDPE area. An existing user may continue because their current ponds remain worthwhile, because changing systems is costly, or because the present configuration fits the farm. None of these reasons necessarily implies an intention to expand.

The behavioral target therefore needs a physical baseline. Intention to expand concerns an increase from the household's current HDPE-lined area, not a general willingness to use HDPE. It is also distinct from an increase in HDPE's percentage share caused solely by reducing other pond area. This definition makes the dependent variable interpretable as planned additional deployment. It keeps the article's claims within the selected population: current users with operating experience. Associations in that population cannot directly explain why non-users have not adopted HDPE or why previous users abandoned it.

What Existing Evidence Establishes And Leaves Unresolved

Vietnamese shrimp research indicates that investment and practice adoption are shaped by more than technical performance. Joffre et al. (2019) show that farmer clustering, interactions with supporting actors, and risk perceptions are associated with the adoption of water-quality, feeding, and disease-control practices. Xuan and Sandorf (2020) demonstrate that financing conditions and credit incentives enter farmers' choices over higher-technology shrimp production. Ngoc et al. (2021) further show that expected yield and crop success influence preferences for improved production methods. These studies establish the relevance of social, financial, and expected-performance considerations, but they do not specify a perceived-value pathway for post-adoption HDPE expansion.

A second stream concerns information and competence. Ulhaq et al. (2022), using data from 184 intensive shrimp farmers in Vietnam, report roles for perceived usefulness, peer influence, and confidence in learning technology in ICT adoption intention. In smart-farming networks, Dilleen et al. (2023) find that farmers trust peer-generated online information more than vendor content. Zheng and Wang (2026) provide evidence from fruit production that technology cognition partially transmits the association between social-media use and drone adoption. These findings justify examining information and competence, while their technologies and behavioral outcomes remain distinct from HDPE area expansion.

Recent synthesis reinforces the importance of distinguishing evaluation from realized behavior. Gouroubera et al. (2026), using meta-analytic structural equation modeling across 33 digital-agriculture studies, identify perceived usefulness as a central driver of acceptance and document a persistent intention-use gap. That evidence supports attention to practical value and enabling conditions, but it does not establish that a digital-technology acceptance model can explain expansion of physical pond infrastructure. Table 1 therefore compares the closest evidence at the level of decision, mechanism, and unresolved question.

Table 1. Selected evidence and the unresolved expansion question

Study	Decision and contribution	Question left open
Xuan & Sandorf (2020)	Higher-technology shrimp investment; choice experiments examine capital access and credit incentives.	How perceived financial burden relates to value among experienced HDPE users.
Ngoc et al. (2021)	Improved shrimp production methods in Vietnam; choice experiments examine investment preferences.	How overall value connects competing appraisals to a specific area-expansion intention.
Do & Ho (2022)	Adaptation practices, including plastic pond lining; adoption choices and productivity are examined.	How current HDPE operators evaluate further deployment after production experience.
Ulhaq et al. (2022)	Shrimp ICT adoption intention; usefulness, peer influence and learning confidence are relevant.	Whether operational readiness conditions the value expansion relationship for physical ponds.
Dilleen et al. (2023)	Smart farming networks; interviews and netnography distinguish trust in peer and vendor information.	Whether channel-specific information is associated with HDPE value in a quantitative model.

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Zheng & Wang (2026)	Drone adoption in fruit production; technology cognition mediates the social media association.	Whether this informational pathway transfers to expansion by established pond-technology users.

The gap emerging from this comparison concerns an untested combination of decision stage, mechanism and boundary condition. Existing HDPE users are the decision-makers; additional lined pond area is the intended behavior; perceived value is the proposed channel through which competing considerations relate to that intention; operational readiness is the proposed moderator. The inquiry also separates external production threats from risks created by adopting a technology. The former can increase the attractiveness of a credible protective response, whereas the latter can discourage investment. Treating both as an undifferentiated risk variable would obscure this distinction.

The present article consequently develops a bounded extension rather than claiming an absence of relevant research. Evidence on adaptation, finance, social learning and technology acceptance informs the model. What remains to be tested is whether those insights explain expansion intention in the specified population, and whether a flexible predictive model adds useful information beyond the proposed average relationships.

Theoretical Foundation and Construct Boundaries

The value-based adoption model is the primary theoretical foundation. Kim et al. (2007) conceptualize technology adoption through perceived value formed from the trade-off between benefits and sacrifices. Zeithaml (1988) likewise treats value as an overall evaluation rather than a synonym for price, quality, or a single benefit. Applied here, perceived value is the farmer's overall judgment of whether HDPE is worthwhile for the household's shrimp production after considering what is expected to be gained and what must be given up. It is therefore distinct from expected yield, affordability, or technical capability.

This foundation fits a household investment decision because the decision-maker evaluates a technology whose financial consequences are borne by the household. The application is adapted to production rather than copied from consumer services. Expected economic benefits represent anticipated production and income advantages. Investment and operating cost burden represents financial sacrifice relative to household resources. Social media influence concerns information entering the appraisal. Perceived climate and disease threats concern production vulnerability that may increase the relevance of protective benefits. Operational readiness is placed at the value intention link because a worthwhile option still has to appear manageable.

Protection motivation theory provides a focused rationale for the threat relationship. Rogers (1975) connects protective motivation to a threat's seriousness, likelihood and the efficacy of a protective response. The implication for this model is conditional: perceiving production threats can raise HDPE's value when the farmer regards the system as a credible response to relevant vulnerabilities. The article does not claim to test the full protection motivation framework. Separate response-efficacy and coping-appraisal constructs are not specified in the model, so the threat pathway alone cannot verify that wider theory. Task-specific efficacy reasoning helps define the readiness moderator. Bandura (1977) distinguishes beliefs about one's ability to perform an action from expectations about its outcomes. Technological readiness here means the decision-maker's perceived operational preparedness to manage the HDPE system, including equipment use, water-quality management, routine troubleshooting and learning new procedures. This definition is narrower than the general propensity to embrace technology assessed by Parasuraman's (2000) Technology Readiness Index. The readiness label therefore denotes a context-specific operational construct, not an application of that index or an objective certification of technical competence.

Several boundaries follow. Climate and disease threats are perceptions of exposure and potential production loss, not claims about the measured incidence of either hazard. Social media influence is channel-specific informational influence, not institutional pressure or a general subjective norm. Expected economic benefits are anticipated advantages, not realized profit. Perceived value integrates the appraisal, while expansion intention concerns a prospective increase in lined area. Keeping these boundaries explicit prevents the model from explaining intention with constructs that already contain the same intended behavior.

Expected Economic Benefits and Perceived Value

Expected economic benefits should improve the perceived value of HDPE because they increase what the household anticipates receiving from the production option. Relevant expectations include harvested output, survival, net income and the stability of economic outcomes across cycles. They remain beliefs about future performance. A farmer's expectation of improved survival, for example, is different from a demonstrated reduction in mortality and from the overall judgment that the system is worth its costs.

Agricultural technology research provides a basis for treating anticipated performance as part of the value appraisal. Gouroubera et al. (2026) identify perceived usefulness as a central determinant in farmers' acceptance of digital technologies. In intensive shrimp farming, Ulhaq et al. (2022) likewise report that perceived usefulness

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is associated with ICT adoption intention. The technologies differ from pond lining, so the present model does not transfer their effects directly; instead, it places expected economic gains upstream of the broader perceived-value judgment. This placement allows apparently favorable benefits to coexist with modest value. A household may expect more output yet regard the additional income as insufficient compensation for electricity, maintenance or financing demands. Conversely, a smaller expected output gain may be attractive when the farmer anticipates more reliable returns. The hypothesis concerns the positive contribution of expected benefits to the overall appraisal, with the other value antecedents considered in the model.

H1. Expected economic benefits are positively associated with the perceived value of HDPE-lined shrimp ponds.

Social Media Influence and Perceived Value

HDPE-related exchanges on social media can inform value judgments by making other farmers' experience available for comparison. Social media influence is defined as the perceived decision relevance of information and peer exchanges about HDPE encountered through online social platforms. It concerns the informational channel, including accounts of operating experience and practical discussions. General time spent online does not establish this influence, and expectations expressed by local authorities or buyers are conceptually different.

Evidence supports an informational pathway but does not imply that all online exposure is favorable. Dilleen et al. (2023) show that farmers use social media for discussion and place greater trust in peer content than in smart-farming vendor information. Zheng and Wang (2026) report that technology cognition partially mediates the association between social-media use and drone adoption among fruit farmers. Within Vietnamese shrimp farming, Joffre et al. (2019) demonstrate that interactions with supporting actors are associated with practice adoption, although their study concerns broader networks rather than social media. The channel-specific relationship between online information and HDPE value therefore remains an empirical question. For experienced HDPE users, online exchanges may help compare their own costs and outcomes with those of other operators. Credible accounts can make expected benefits easier to assess and clarify whether operating difficulties are manageable. This supplies a rationale for a positive association with value where information is useful and credible. Reports of failures or exaggerated promotional claims can work in the opposite direction. The hypothesis is therefore an empirical expectation about the proposed informational influence, not a claim that all social media content increases HDPE's attractiveness.

H2. Social media influence is positively associated with the perceived value of HDPE-lined shrimp ponds.

Perceived Climate And Disease Threats And Perceived Value

Perceived production threats can increase the value attached to a protective production option. The construct captures the decision-maker's perception that adverse weather, climate-related water conditions or disease can cause substantial losses to the household's shrimp production. Climate and disease are related sources of production vulnerability, but their inclusion under one label does not make them interchangeable. The proposed common construct must retain that content distinction when it is subsequently evaluated.

The direction of this relationship depends on the source of risk. Jayashankar et al. (2018) examine technology-related risk in agricultural IoT adoption and report a negative relationship with adoption. The present threat construct concerns harmful conditions faced by the production activity, rather than a perceived risk created by purchasing HDPE. Under protection motivation reasoning, a more serious external threat can make a credible protective response more valuable (Rogers, 1975). A positive direction is therefore plausible without contradicting evidence that technology-specific investment risks discourage adoption. Regional evidence establishes the relevance of perceived climate and disease vulnerability without implying that HDPE provides complete protection. Do and Ho (2022) show that beliefs about climatic change and its effects are important in shrimp farmers' adaptation choices. Le et al. (2024) identify climatic events, farm characteristics, and management practices as determinants of disease occurrence in intensive white-leg shrimp farms. These studies justify treating external production threats as part of the investment context, but neither demonstrates that pond lining eliminates climatic stress or disease risk.

The positive hypothesis rests on farmers regarding HDPE-based management as useful for addressing some of the vulnerabilities they perceive. Greater concern would then increase the importance attached to those perceived protective benefits in the overall value judgment. If farmers regard HDPE as ineffective against the threats they face, the association may be absent or negative; severe threats can also make any expansion unattractive. The hypothesis specifies the protective-value expectation and leaves these competing possibilities for empirical assessment.

H3. Perceived climate and disease threats are positively associated with the perceived value of HDPE-lined shrimp ponds.

Investment and Operating Cost Burden and Perceived Value

Financial burden should reduce perceived value when expenditure strains the household relative to the benefits it anticipates. The construct includes the perceived burden of additional investment, recurring operation,

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repair or liner replacement, and limited financial capacity to sustain the system. It is broader than the purchase price of the liner. It also differs from an objective cost measure: two households facing similar expenditure may perceive different burdens because their resources and financing conditions differ.

Vietnamese aquaculture evidence supports treating financial burden as distinct from expected production benefit. Xuan and Sandorf (2020) show that credit subsidies and access to capital can alter willingness to invest in higher-technology shrimp production. Ngoc et al. (2021) likewise locate investment preferences within trade-offs among improved production attributes and financing conditions. These studies do not test the psychological pathway proposed here, but they demonstrate why a household's financial appraisal cannot be inferred from expected production gains alone.

The value mechanism concerns sacrifice relative to expected benefit. When recurring expenditure is difficult to carry or further installation threatens household liquidity, the system can appear less worthwhile even if the farmer expects favorable production outcomes. For example, an operator may anticipate higher output from an additional lined pond but place less value on that prospect if it leaves too little capital to sustain the next cycle. The proposed association therefore addresses the burden that financial commitments place on the overall appraisal, rather than assuming that a high absolute price always indicates low value.

H4. Investment and operating cost burden is negatively associated with the perceived value of HDPE-lined shrimp ponds.

Perceived Value and Expansion Intention

Perceived value should support expansion intention because it provides an overall reason to commit additional pond area to HDPE. Kim et al. (2007) position perceived value as a direct antecedent of adoption intention in the value-based adoption model. In agriculture, Jayashankar et al. (2018) report a positive relationship between perceived value and IoT adoption. Extending this logic to experienced HDPE users requires a narrower behavioral target: the favorable appraisal must justify an additional investment rather than merely reflect satisfaction with the current system.

This translation is plausible but incomplete. Existing use supplies experience that can inform the appraisal; expanding the system still requires new resource commitments. A household may regard HDPE as worthwhile at its current scale while expecting weaker returns from another pond or facing limits on usable area. Thus, overall value is proposed as an antecedent of expansion intention, not as a sufficient condition for expansion. The readiness moderator addresses one part of this distinction, while resource constraints remain relevant to interpreting the relationship.

Perceived value also supplies the connecting pathway from the four antecedents to intention. Combining H1–H5 implies positive indirect associations for expected benefits, social media influence and production threats, and a negative indirect association for cost burden through value. These implications follow from the model rather than constitute separate claims about established mediation. The specified pathway prioritizes value as the connecting mechanism; evidence on indirect associations would not, by itself, rule out additional direct pathways or reverse relationships.

The outcome remains an intention. A favorable value appraisal and a stronger intention do not establish that pond area subsequently increased, that the investment produced higher profit, or that environmental performance improved. Those outcomes would require different evidence. Keeping the behavioral claim at the intention level is especially important for relating the study to investment or extension decisions.

H5. Perceived value is positively associated with the intention to expand HDPE-lined shrimp pond area.

The Moderating Role Of Technological Readiness

Perceived operational readiness should strengthen the association between value and expansion intention. A farmer who considers HDPE worthwhile still needs confidence that the additional area can be managed. Task-specific efficacy reasoning distinguishes that confidence from expected returns (Bandura, 1977). In this model, readiness concerns perceived ability to operate equipment, manage water conditions, handle routine technical problems and learn relevant procedures. It is not defined by the farmer's intention to invest or by their general enthusiasm for technology.

Existing use does not remove the distinction. Managing current ponds can provide experience, yet adding another pond may reveal limits in the decision-maker's perceived capacity to supervise operations or respond to simultaneous problems. For a farmer with higher readiness, a favorable value assessment may more readily become a concrete plan to increase area. With lower readiness, the same assessment may support retaining the present configuration while the farmer postpones further deployment. This is an amplification argument: readiness makes a positive appraisal more actionable.

The shrimp ICT evidence provides a related but narrower basis. Ulhaq et al. (2022) connect confidence in learning new technology with technology evaluations. The proposed hypothesis extends the role of competence beliefs to the translation of value into expansion intention. It does not assert that those authors established the

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interaction for HDPE. Nor does a positive association between readiness and intention establish moderation. Moderation specifically requires the value intention association to become stronger as readiness increases.

H6. Technological readiness positively moderates the relationship between perceived value and expansion intention, such that the positive association is stronger at higher levels of readiness.

Figure 1 integrates the six hypotheses. Four antecedents are linked to perceived value, which is linked to expansion intention. Technological readiness conditions the latter relationship. The proposed interaction also implies that the strength of the indirect associations transmitted through value can vary with readiness.

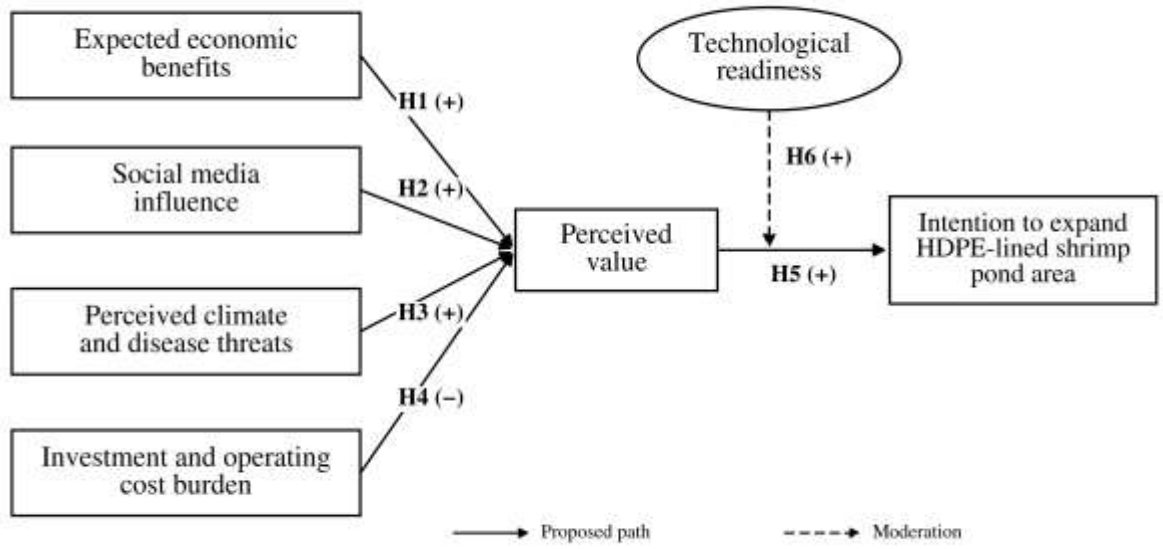


Figure 1. Proposed research model

The hybrid approach asks whether the theory-specified average relationships are sufficient for prediction. PLS-SEM addresses the proposed construct relationships, but predictive performance on new observations must be evaluated separately; Shmueli et al. (2019) provide holdout-oriented guidance for this purpose in PLS-SEM. XGBoost offers a flexible prediction function that can capture nonlinearities and interactions without imposing the same structural form as the path model (Chen & Guestrin, 2016). The two analyses are therefore complementary rather than interchangeable.

The comparison is a methodological audit of model specification, validation, and interpretability; it does not assume that a hybrid workflow delivers superior prediction. Explainable machine learning has been used in related aquaculture forecasting (Wu et al., 2024), but the present outcome is household intention rather than realized production or market prices.

SHAP is used to interpret the fitted prediction function rather than to infer causality. Lundberg and Lee (2017) introduce a unified additive feature-attribution framework for individual predictions. For tree-based models, Lundberg et al. (2020) show how such local attributions can be aggregated to reveal broader model structure. In this study, SHAP may indicate which measured inputs contribute most to predicted expansion intention and how those contributions vary across observed values, even when the corresponding average PLS-SEM path is modest.

METHODOLOGY

Research Design

The study used a sequential survey design with questionnaire refinement, pilot testing, field data collection, and hybrid explanatory predictive analysis. Measurement items were adapted from previous studies and reviewed by four experts to ensure suitability for HDPE-lined shrimp farming. The experts included two PhD-level aquaculture academics from leading Vietnamese universities and two aquaculture engineers with more than eight years of practical experience. Their comments were used to improve the wording, technical terms, and relevance of the items. All constructs were measured using a 5-point Likert scale.

The pilot survey was conducted through Google Forms and collected 57 responses by 11th May 2026 . It was used to check questionnaire clarity, response consistency, and preliminary scale quality. After revision, the main field survey was carried out from 7th June to 13th September 2026, in post-merger Can Tho City, covering the former Can Tho, Soc Trang, and Hau Giang areas. Respondents were shrimp-farming household decision-makers who had experience with HDPE-lined ponds and had completed at least one production cycle. After screening and data cleaning, 356 valid questionnaires were retained. As shown in Figure 2, PLS-SEM was used to

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assess the measurement model and test structural relationships. Latent variable scores were then used in XGBoost for prediction. The dataset was divided into training and testing sets, while SHAP was applied to explain variable contributions and possible nonlinear patterns. This design separates theory testing from prediction and provides a clearer analysis of expansion intention.

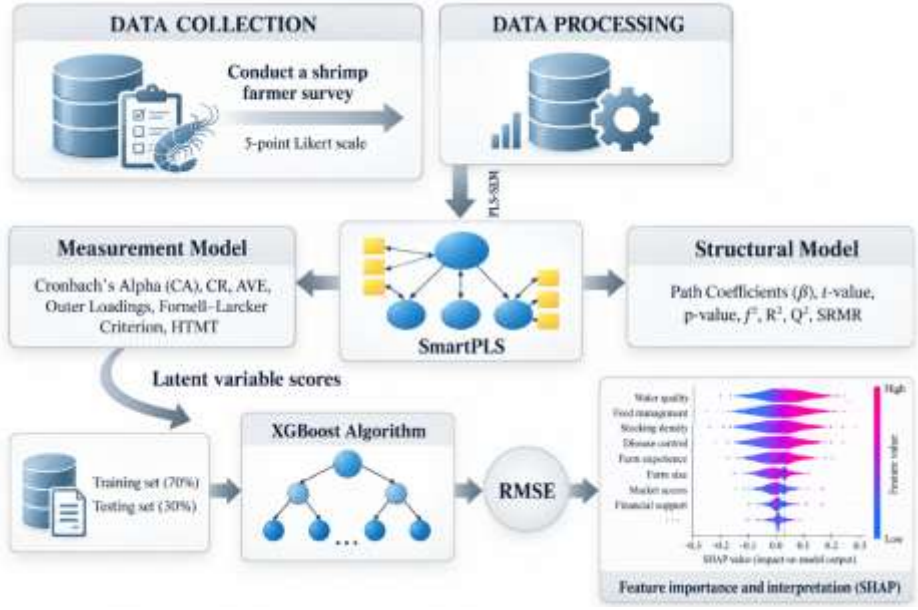


Figure 2. Research Procedure

Sampling And Data Collection

Figure 3 presents the study area for data collection in post-merger Can Tho City, which was divided into three survey areas: Can Tho, Hau Giang, and Soc Trang. This division helps capture differences in production conditions, experience in operating HDPE-lined ponds, and the level of shrimp-farming development across the subareas within the new administrative area. Data were collected directly from shrimp-farming households currently operating HDPE-lined ponds. Respondents were individuals involved in household investment decisions and farm management. The questionnaire used a 5-point Likert scale, ranging from 1 = strongly disagree to 5 = strongly agree, to measure farmers' perceptions of expected economic benefits, social information influence, climate and disease risks, cost burden, technological readiness, perceived value, and intention to expand HDPE-lined pond area.



Figure 3. Study area in post-merger Can Tho City

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The pilot survey results in Table 2, based on 57 responses, showed that the measurement scales achieved acceptable preliminary reliability before the main survey. Cronbach's alpha values ranged from 0.774 to 0.832, all above the recommended threshold of 0.70. The lowest corrected item–total correlation was 0.501, indicating that the items were reasonably consistent with their respective constructs. Preliminary factor loadings ranged from 0.681 to 0.846, with no item showing an unacceptably low loading. These results suggest that the questionnaire had stable initial measurement quality, and no item needed to be removed at the pilot stage.

Table 2. Preliminary Measurement Assessment (Pilot, N = 57)

Construct	Items	α	CITC	Loading range	Assessment
Expected economic benefits (EVE)	4	0.814	0.562	0.704–0.832	Accepted
Social media influence (SMI)	4	0.786	0.524	0.691–0.815	Accepted
Perceived climate and disease threats (PCD)	5	0.823	0.548	0.683–0.824	Accepted
Technological readiness (TR)	4	0.801	0.536	0.712–0.829	Accepted
Investment and operating cost burden (CCB)	4	0.774	0.501	0.681–0.793	Accepted
Perceived value (PV)	4	0.832	0.587	0.729–0.846	Accepted
Intention to expand HDPE-lined pond area (EI)	3	0.798	0.566	0.738–0.842	Accepted

After the pilot survey confirmed acceptable preliminary reliability and stability of the measurement scales, the study proceeded with the main survey through direct field data collection. The author was directly involved in and supervised the data collection process to ensure that respondents met the study criteria and to reduce possible errors during data collection. After screening and checking the completeness of the questionnaires, 356 valid responses were retained for the final analysis. The characteristics of the study sample are presented in Table 3.

Table 3. Sample Characteristics (N = 356)

Characteristic	Category	Frequency (n)	Percentage (%)
Survey area	Soc Trang	189	53.1
	Can Tho	92	25.8
	Hau Giang	75	21.1
Gender	Male	249	69.9
	Female	107	30.1
Age	18–30 years	44	12.4
	31–40 years	113	31.7
	41–50 years	121	34.0
	51–62 years	78	21.9
Shrimp farming experience	Less than 5 years	58	16.3
	5–10 years	136	38.2
	11–15 years	99	27.8
	More than 15 years	63	17.7
Year of first HDPE use	≤ 2020	72	20.2
	2021–2022	104	29.2
	2023–2024	126	35.4
	2025–2026	54	15.2
Number of HDPE production cycles completed	1–2 cycles	65	18.3
	3–5 cycles	154	43.3
	6–8 cycles	88	24.7
	More than 8 cycles	49	13.8
Total shrimp farming area	≤ 1 ha	76	21.3
	1.01–2 ha	132	37.1
	2.01–3 ha	91	25.6
	> 3 ha	57	16.0
Share of HDPE-lined pond area in total farming area	< 25%	48	13.5
	25–49%	96	27.0
	50–74%	132	37.1
	≥ 75%	80	22.5

Table 3 shows that the sample is concentrated among farmers with substantial production experience and meaningful exposure to HDPE-lined ponds, which fits the study's focus on post-adoption expansion intention. Soc Trang accounts for 53.1% of the sample, compared with 25.8% from Can Tho and 21.1% from Hau Giang, indicating that the survey is weighted toward an area with stronger shrimp-farming activity. Most respondents are also in active working-age groups, with 65.7% aged 31–50 years, while 66.0% have 5–15 years of shrimp-farming

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experience. This suggests that the majority of respondents have enough practical experience to assess the benefits, costs, and risks of HDPE systems.

In addition, 79.8% of households started using HDPE after 2020, and 81.8% had completed at least three HDPE production cycles. This indicates that HDPE use had moved beyond an initial trial stage for most respondents. In terms of farm structure, 78.7% operated more than 1 ha of shrimp-farming area, while 59.6% had at least 50% of their farming area covered by HDPE-lined ponds. These patterns suggest that HDPE has become an important part of the production system for many households, making further expansion a substantive investment decision rather than a simple technology trial.

Measurement Instrument

The measurement instrument was developed based on the constructs in the proposed research model and adapted to the context of expanding HDPE-lined shrimp ponds. The measurement items, codes, and sources are presented in Table 4.

To examine whether perceived climate threats and perceived disease threats should be distinguished, an exploratory score-based specification was defined using PCD1, PCD2, and PCD5 for climate/water threats and PCD3 and PCD4 for disease threats. Because the latter dimension contains only two original indicators, this reclassification is a sensitivity analysis rather than a validated replacement measurement model. Neither additional questionnaire items nor new respondents were introduced.

Table 4. Measurement Items

Construct	Code	Measurement item	Source
Expected economic benefits	EVE1	I expect HDPE-lined ponds to increase shrimp output in each production cycle.	Ngoc et al. (2021); Ulhaq et al. (2022)
	EVE2	I expect HDPE-lined ponds to improve shrimp survival rates.	
	EVE3	I expect HDPE-lined ponds to increase net income from shrimp farming.	
	EVE4	I expect HDPE to make my farm's economic results more stable across production cycles.	
Social media influence	SMI1	Information about HDPE on social media helps me evaluate its economic and operational benefits.	Joffre et al. (2019); Dilleen et al. (2023); Zheng & Wang (2026)
	SMI2	Experiences shared by other shrimp farmers on social media influence how I evaluate HDPE-lined ponds.	
	SMI3	Discussions in online shrimp-farming groups affect my view of whether expanding HDPE-lined pond area is worthwhile.	
	SMI4	I consider information from experienced farmers on social media when deciding whether to expand HDPE-lined pond area.	
Perceived climate and disease threats	PCD1	I perceive extreme weather and climate variability as serious threats to my shrimp farming activities.	Do & Ho (2022); Le et al. (2024)
	PCD2	I perceive changes in water conditions, such as salinity or temperature, as serious threats to my shrimp farming outcomes.	
	PCD3	I perceive disease as a serious threat to my shrimp farming activities.	
	PCD4	A serious disease outbreak could cause substantial losses in shrimp output or household income.	
	PCD5	Adverse climate or water conditions could cause substantial losses in shrimp output or household income.	
Technological readiness	TR1	I have sufficient ability to operate the main equipment used in an HDPE pond system.	Ulhaq et al. (2022); Bandura (1977)
	TR2	I have sufficient ability to monitor and adjust water quality when operating HDPE-lined ponds.	
	TR3	I have sufficient ability to handle common technical problems when operating HDPE-lined ponds.	

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	TR4	I have sufficient ability to learn and apply new technical procedures for operating HDPE-lined ponds.	
Investment and operating cost burden	CCB1	The capital required to expand or upgrade the HDPE pond system would create financial pressure on my household.	Xuan & Sandorf (2020); Ngoc et al. (2021)
	CCB2	The recurring costs of operating the HDPE system, such as electricity and water treatment, are difficult for my household to bear.	
	CCB3	The costs of repairing or replacing HDPE liners and related facilities create a substantial financial burden for my household.	
	CCB4	My household's current financial resources are limited for maintaining or upgrading the HDPE pond system when needed.	
Perceived value	PV1	Considering the benefits received and what my household must give up, HDPE-lined ponds are a worthwhile option.	Kim et al. (2007); Zeithaml (1988); Jayashankar et al. (2018)
	PV2	The benefits of HDPE are worth the financial and operating costs required.	
	PV3	HDPE provides good value for my household's shrimp farming activities.	
	PV4	Compared with other pond systems available to my household, HDPE provides higher overall value.	
Intention to expand HDPE-lined shrimp pond area	EI1	I intend to increase the total area of HDPE-lined shrimp ponds in future production cycles.	Ajzen (1991)
	EI2	If I develop additional pond area or convert existing earthen ponds, I intend to use HDPE lining.	
	EI3	I plan to add or convert pond area so that the absolute area of HDPE-lined ponds on my farm increases.	

The data showed adequate factorability, with a KMO value of 0.815 and a significant Bartlett's test of sphericity ($\chi^2 = 3{,}159.660$, df = 378, $p < 0.001$). Harman's single-factor test indicated that the first factor accounted for only 17.51% of the total variance, well below the 50% threshold. In addition, full collinearity VIF values ranged from 1.084 to 1.680, remaining below the recommended threshold of 3.3 (Kock, 2015). These diagnostics do not establish the absence of common-method bias, because all explanatory and outcome measures were obtained from the same self-reported survey at one point in time.

The documented design involved expert review of item wording, a separate pilot survey, eligibility screening, and direct field supervision of data collection. These procedures addressed item clarity and respondent eligibility but cannot be equated with independently measured outcomes, temporal separation, or statistical elimination of common-source bias. No unrecorded anonymity, randomized item ordering, or marker-variable procedure is claimed.

Table 5. Common Method Bias and Factorability Assessment

Test	Indicator	Result	Recommended criterion	Assessment
KMO	Kaiser–Meyer–Olkin	0.815	> 0.70	Good
Bartlett's Test	Approx. χ^2	3,159.660	—	—
	df	378	—	—
	Sig.	< 0.001	< 0.05	Significant
Harman's single-factor test	Variance explained by the first factor	17.51%	< 50%	No serious indication of CMB
Full collinearity VIF	Minimum VIF	1.084	< 3.30	Acceptable
	Maximum VIF	1.680	< 3.30	Acceptable

RESULT ANALYSIS

Measurement Model Assessment

The results in Table 6 show that the measurement model generally meets the required levels of reliability and convergent validity. Cronbach's alpha, rho_A, and composite reliability values for all constructs exceed the

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acceptable thresholds, while AVE ranges from 0.559 to 0.657, indicating sufficient variance explained by the observed indicators. Most outer loadings are at acceptable levels, although PCD1, CCB2, and particularly TR3 fall below 0.70 (Hair et al., 2022). Even so, the related constructs still maintain adequate CR and AVE values, suggesting that retaining these items does not substantially weaken the measurement model. Overall, the measurement scales show sufficient stability to proceed with discriminant validity and structural model assessment.

TR3 (0.566), PCD1 (0.636), and CCB2 (0.658) were retained in the published specification to preserve task-specific troubleshooting capacity, climate-weather exposure, and recurrent operating-cost content, respectively. Reliability and convergent-validity statistics were acceptable at the construct level, but these statistics do not remove concern about weak individual indicators. The following supplementary item-deletion analysis evaluates sensitivity rather than treating a numerical cut-off as sufficient justification.

Table 6. Item Loadings and Reliability Measures

Latent Variable	Obs. Var	Outer Loading	Cronbach's Alpha	rho_A	CR	AVE
Expected Economic Benefits	EVE1	0.798	0.781	0.788	0.858	0.602
	EVE2	0.787				
	EVE3	0.766				
	EVE4	0.751				
Social Media Influence	SMI1	0.780	0.778	0.787	0.857	0.599
	SMI2	0.820				
	SMI3	0.741				
	SMI4	0.754				
Perceived Climate and Disease Threats	PCD1	0.636	0.814	0.842	0.863	0.559
	PCD2	0.777				
	PCD3	0.796				
	PCD4	0.723				
	PCD5	0.795				
Technological Readiness	TR1	0.751	0.792	0.832	0.840	0.574
	TR2	0.778				
	TR3	0.566				
	TR4	0.898				
Investment and Operating Cost Burden	CCB1	0.774	0.760	0.778	0.841	0.571
	CCB2	0.658				
	CCB3	0.814				
	CCB4	0.768				
Perceived Value (PV)	PV1	0.789	0.794	0.795	0.866	0.618
	PV2	0.795				
	PV3	0.758				
	PV4	0.801				
Expansion Intention (EI)	EI1	0.804	0.739	0.740	0.852	0.657
	EI2	0.811				
	EI3	0.817				

The HTMT results in Table 7 show that all construct pairs are below the 0.85 threshold, with the highest value being 0.731 between PV and EI. This confirms adequate discriminant validity, indicating that the constructs are empirically distinct and suitable for further structural model analysis (Henseler et al., 2015).

Table 7. Heterotrait–monotrait ratio (HTMT)

Construct	CCB	EI	EVE	PCD	PV	SMI	TR
CCB							
EI	**0.224**						
EVE	0.093	**0.375**					
PCD	0.183	0.198	**0.083**				
PV	0.267	0.731	0.439	**0.199**			
SMI	0.115	0.299	0.211	0.094	**0.388**		
TR	0.096	0.115	0.064	0.151	0.130	**0.297**	

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Structural Model Assessment

The structural model results show that perceived value is the central mechanism driving expansion intention, with the strongest effect on EI (β = 0.568; f^2 = 0.515). This suggests that farmers are unlikely to expand HDPE-lined pond area because of a single benefit alone; they are more likely to invest further when the overall benefits are judged to outweigh the associated costs and risks. In forming this value assessment, expected economic benefits have the strongest positive effect (β = 0.294), while cost burden significantly reduces perceived value (β = −0.213). This indicates that expected economic returns and financial pressure are the two most important practical considerations in the expansion decision.

A notable result is the negative effect of the PV × TR interaction (β = −0.191; p = 0.001), which is opposite to the hypothesized positive moderation. One possible explanation is that technically prepared farmers may be more aware of constraints on further expansion; the cross-sectional responses do not directly measure such a caution mechanism. Therefore, H1–H5 are supported, while H6 is not supported in the originally hypothesized direction.

Table 8. PLS Structure Model Results

Hyp.	Path	β	t	p	95% BCa CI	f^2
H1	EVE → PV	0.294	6.913	<0.001	[0.202, 0.364]	0.113
H2	SMI → PV	0.229	4.912	<0.001	[0.141, 0.317]	0.068
H3	PCD → PV	0.178	3.777	<0.001	[0.088, 0.257]	0.042
H4	CCB → PV	−0.213	5.369	<0.001	[−0.288, −0.132]	0.059
H5	PV → EI	0.568	15.582	<0.001	[0.489, 0.622]	0.515
H6	PV × TR → EI	−0.191	3.276	0.001	[−0.280, −0.100]	0.066

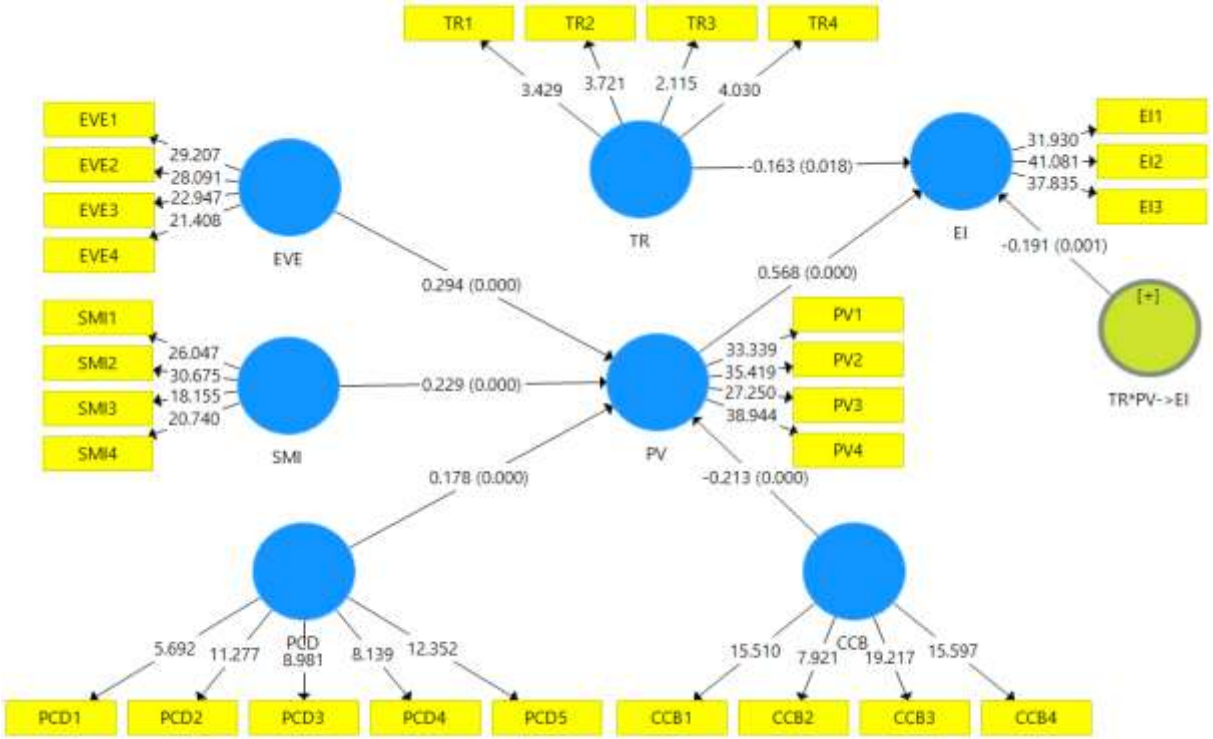


Figure 4. Structural Model

A possible, but unverified, interpretation is that technically prepared farmers recognize marginal costs, water-management pressures, and scaling constraints more clearly. Therefore, greater technical experience may shift farmers from simply "trusting the technology" toward a more selective investment assessment.

This finding also helps distinguish technology adoption from post-adoption expansion. At the initial adoption stage, technological readiness is often treated as a facilitating factor. After farmers gain actual operating experience, however, readiness may instead be associated with more selective expansion intentions; experience-based caution remains a hypothesis for future testing.

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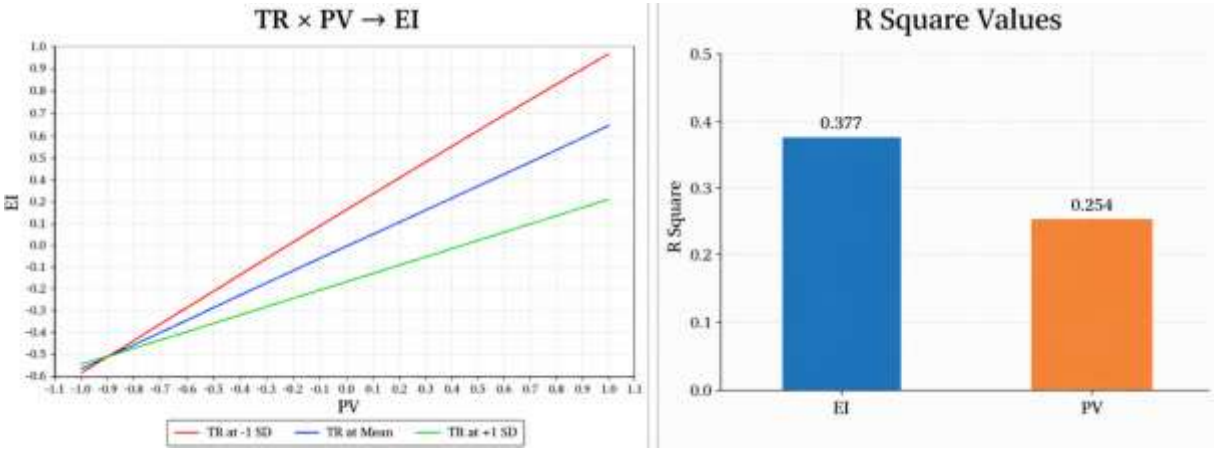


Figure 5. Moderating Effect of Technological Readiness and Explained Variance of the Structural Model

Figure 5 illustrates that technological readiness does not strengthen but instead weakens the effect of perceived value on expansion intention, creating an important moderating pattern. When TR is low, the relationship between PV and EI is the steepest. As TR increases to the mean level and +1 SD, the slope becomes clearly weaker. This suggests that perceived value matters more for farmers with lower technical readiness, while farmers with higher readiness rely less on the simple judgment of whether HDPE is "worthwhile" when deciding to expand. For technically experienced farmers, expansion decisions may depend more on operational limits, the ability to manage multiple ponds, working capital, or the risks of scaling up. This pattern may reflect a form of experience-based caution at the post-adoption stage.

In terms of explanatory power, the model explains 37.7% of the variance in EI, while the antecedent variables explain 25.4% of the variance in PV. The higher R^2 for EI suggests that once perceived value has been formed, adding TR and the PV×TR interaction helps explain a meaningful part of the variation in expansion intention. In contrast, the R^2 of 0.254 for PV indicates that farmers' value assessments are still influenced by other factors outside the model, such as actual production outcomes, credit conditions, farm size, or output price fluctuations.

XGBoost–SHAP Analysis

After testing the theoretical relationships using PLS-SEM, the study applied XGBoost–SHAP to assess predictive performance and identify possible nonlinear patterns that may not be captured by the linear structural model. XGBoost was used to predict expansion intention, while SHAP was applied to evaluate the contribution of each predictor and explain how the variables influenced the model output. These predictive results complement, rather than replace, the structural evidence obtained from PLS-SEM.

Supplementary predictive validation used the 356-by-28 item-level dataset and arithmetic item-mean scores for each construct. These score-based analyses are independent of, and do not replace, the originally reported SmartPLS estimates. In a repeated five-fold outer cross-validation with three repeats (15 outer test folds), XGBoost settings were chosen using three-fold inner cross-validation on each outer training partition from six pre-specified candidate configurations. Linear models and XGBoost were evaluated on identical outer test folds, with predictive R^2, root mean squared error, and mean absolute error recorded. The six construct scores were derived within each household using the relevant questionnaire items; no outcome observations from the outer test fold entered model training or tuning. The original 70/30 holdout analysis is retained as a separate result (Table 10).

This supplementary nested validation uses item-mean scores, not newly estimated cross-validated latent variable scores. It therefore supports the relative score-based predictive comparison while leaving a full fold-wise re-estimation of the SmartPLS measurement model for future work. Recent reviews of predictive modeling in agriculture emphasize transparent validation and comparison against simpler alternatives (Jabed & Murad, 2024; Shawon et al., 2025).

Table 9. XGBoost Setup Parameters

Parameter	Function / setting
Training / holdout	70% / 30% (n = 249 / 107), random seed = 42
Predictors	EVE, SMI, PCD, TR, CCB, and PV construct scores
Outcome	EI construct score
Hyperparameter search	Grid search with 10-fold cross-validation within training data only
Objective	reg:squarederror

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Best n_estimators / max_depth	100 / 3
learning_rate	0.05
subsample / colsample_bytree	0.80 / 0.80
min_child_weight / gamma	3 / 0
reg_lambda	5
Final evaluation	R^2, RMSE, and MAE on untouched 30% holdout

As shown in Table 9, the data were divided into 70% training data (n = 249) and 30% holdout data (n = 107). Hyperparameter tuning was conducted only within the training set using 10-fold cross-validation, reducing the risk of information leakage. The final configuration, including max_depth = 3, learning_rate = 0.05, subsample = 0.80, and colsample_bytree = 0.80, kept the model relatively parsimonious and helped control overfitting. The holdout set was used only for the final evaluation using R^2, RMSE, and MAE.

Table 10. Out-of-sample predictive performance

Model	Holdout R^2	RMSE	MAE
Linear additive benchmark	0.218	0.835	0.690
Theory-informed linear benchmark (+ PV×TR)	0.283	0.799	0.649
Tuned XGBoost	0.163	0.863	0.704

Table 10 shows that the theory-informed linear model with the PV × TR interaction provides the best out-of-sample predictive performance, with R^2 = 0.283, RMSE = 0.799, and MAE = 0.649. It outperforms both the basic linear benchmark and the tuned XGBoost model, indicating that the theoretically specified moderation structure contributes not only to explanation but also to prediction. In contrast, XGBoost achieves a lower R^2 of 0.163 and higher prediction errors. This suggests that greater model flexibility does not provide additional predictive value in this dataset. The main predictive signal therefore appears to be captured more effectively by the linear interaction structure than by more complex nonlinear relationships.

Table 11. Global SHAP importance

Feature	Mean |SHAP|	Share
PV	0.4125	43.6%
TR	0.1417	15.0%
EVE	0.1187	12.5%
PCD	0.0931	9.8%
CCB	0.0930	9.8%
SMI	0.0881	9.3%

Table 11 shows that Perceived Value (PV) is the dominant predictive signal, accounting for 43.6% of total SHAP importance, which is almost three times higher than Technological Readiness (15.0%). This indicates that expansion intention is mainly differentiated by how farmers evaluate the overall value of HDPE, while expected benefits, climate and disease threats, cost burden, and social media influence play more supporting roles. Notably, TR ranks second in predictive importance, although its direct linear effect is weaker than that of PV. This suggests that technological readiness may matter mainly through interaction or nonlinear effects, which is consistent with the PV × TR moderation identified in the PLS-SEM results.

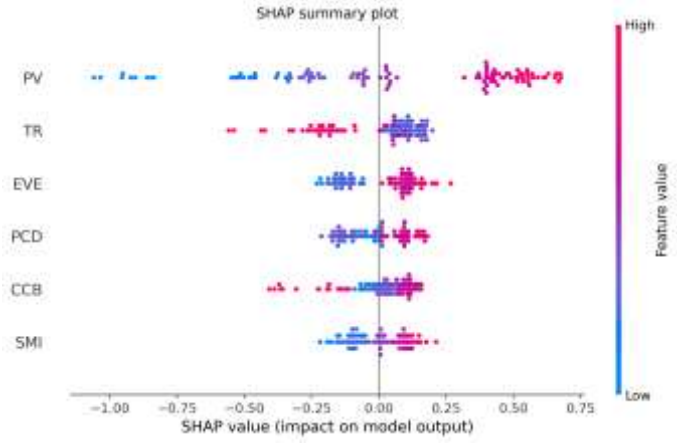


Figure 6. SHAP summary plot

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The SHAP plot highlights three key signals. PV shows the strongest separation: high values clearly push predicted EI upward, while low values produce substantial negative contributions. TR displays the opposite pattern, with higher readiness mainly associated with negative SHAP values, supporting the possibility of experience-based caution at the post-adoption stage. CCB also shows a clear adverse effect as cost burden increases. EVE, PCD, and SMI have smaller effects and remain more concentrated around the center. Overall, the prediction of expansion intention appears to be driven mainly by overall value assessment, technological readiness, and financial burden, rather than by individual benefits or information signals alone.

Table 12. Supplementary nested predictive validation

Model	Mean test R^2 (SD)	Mean RMSE (SD)	Mean MAE (SD)
Linear additive	0.295 (0.112)	0.812 (0.028)	0.675 (0.034)
Linear with PV × TR	0.338 (0.113)	0.786 (0.031)	0.643 (0.038)
Nested-tuned XGBoost	0.292 (0.106)	0.814 (0.034)	0.670 (0.037)

Across the 15 outer test folds, the interaction-informed linear model exceeded XGBoost in test R^2 in 13 folds; its mean R^2 advantage was 0.046. This paired comparison supports the original holdout ranking but does not imply that the observed difference will hold in an external regional sample. The 15 fold outcomes are correlated because training and test observations are reused across repetitions, so the fold standard deviations must not be interpreted as independent-sample confidence intervals.

Table 13. Indicator-deletion sensitivity

Retained indicators	PV → EI (std.)	PV × TR → EI (std.)	EI R^2
All original items	0.486	−0.190	0.396
Without TR3	0.479	−0.183	0.398
Without PCD1	0.483	−0.188	0.397
Without CCB2	0.483	−0.190	0.397
Without all three	0.472	−0.181	0.399

The negative interaction persisted after excluding each low-loading item separately or all three together (standardized score-based coefficients from −0.181 to −0.190). In the full-item score model, a 1,500-resample nonparametric bootstrap gave a 95% percentile interval of [−0.258, −0.115] for the standardized interaction. These supplementary ordinary-least-squares coefficients are not interchangeable with SmartPLS bootstrapped path estimates in Table 8.

Table 14. Exploratory climate–disease separation

Threat score	Original indicators	Standardized link with PV
Climate and water	PCD1, PCD2, PCD5	0.072
Disease	PCD3, PCD4	0.105

The exploratory climate–disease scores correlated at r = 0.679. When both dimensions entered a score-based regression for perceived value alongside economic benefits, social-media influence, and cost burden, their standardized coefficients were 0.072 (climate/water) and 0.105 (disease), with model R^2 = 0.238. The shared variance and two-item disease dimension preclude claiming that this exploratory split establishes two discriminantly valid first-order PLS constructs; confirmatory re-estimation and additional disease indicators are needed.

As an exploratory descriptive subgroup check, the standardized perceived-value coefficient in otherwise comparable score-based regressions was 0.559 for respondents at or below the median readiness score (n = 187) and 0.406 above the median (n = 169). These subgroup patterns are compatible with the full-sample negative interaction but do not establish experience-based caution or a causal mechanism.

DISCUSSION

Interpretation of Main Findings

The results position perceived value as the decision filter through which experienced farmers translate heterogeneous signals into a judgment about whether further HDPE investment is worthwhile. This is more consequential than simply showing that perceived value predicts intention. The sample consists of current HDPE users, so the relationship is observed after farmers have already acquired operating experience. A favorable view of the technology at the present scale does not automatically imply support for additional pond area. The strong PV–EI relationship therefore suggests that expansion is governed by a renewed investment appraisal rather than by inertia from prior adoption. This extends the value-based adoption logic of Kim et al. (2007) and the agricultural

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evidence of Jayashankar et al. (2018) to a post-adoption setting in which the relevant choice is not whether to use a technology, but whether to commit further land, capital, and management capacity to it.

The antecedent pattern clarifies what enters that appraisal. Expected economic benefits and cost burden work in opposite directions, indicating that farmers do not evaluate HDPE through expected production gains alone. The practical decision is closer to a household-level risk–return calculation in which anticipated output, survival, income stability, liquidity pressure, recurring operating costs, and replacement obligations are jointly weighed. This interpretation is consistent with Vietnamese shrimp evidence showing that expected production outcomes and financing conditions shape investment choices (Xuan & Sandorf, 2020; Ngoc et al., 2021). The contribution here is to connect those considerations to a single evaluative mechanism. An attractive technology can therefore remain unexpanded when the next unit of investment places disproportionate pressure on household resources.

The positive associations of social-media influence and perceived climate and disease threats with value reveal two different routes into the same appraisal. Social media appears to function primarily as an information and benchmarking channel. For experienced users, peer reports can be compared with their own operating outcomes, reducing uncertainty about whether observed costs or technical difficulties are farm-specific or more general. This is compatible with evidence that peer-generated information is influential in smart-farming networks (Dilleen et al., 2023) and that social media can shape technology cognition in agriculture (Zheng & Wang, 2026). The threat result requires a different interpretation. It does not mean that risk generally stimulates investment. The measured threats are external production hazards, whereas technology-specific investment risk is a sacrifice. Under protection-motivation reasoning, external threats can raise the value of a response when that response is regarded as capable of reducing exposure or improving control (Rogers, 1975). The finding therefore supports a distinction between the threat facing the production system and the risk created by the investment itself.

The most theoretically informative result is the negative PV × TR interaction. The hypothesis expected technological readiness to make favorable value judgments more actionable, yet the observed pattern shows the opposite: the marginal association between perceived value and expansion intention becomes weaker as readiness rises. This should not be interpreted as evidence that technological capability is harmful. A more plausible reading is that greater operational knowledge changes the decision rule. Farmers with lower readiness may rely more heavily on a broad judgment that HDPE is worthwhile, whereas technically capable farmers can separate overall value from the specific constraints of scaling simultaneous pond supervision, water-quality control, equipment reliability, labor, energy demand, and working-capital exposure. Readiness may therefore shift decision-making from a value-based heuristic toward a constraint-sensitive investment calculation. This “experience-based caution” interpretation is consistent with Bandura’s (1977) distinction between efficacy beliefs and outcome expectations, while showing that competence can operate as a boundary condition rather than a simple accelerator at the post-adoption stage.

Sensitivity estimates and the descriptive readiness subgroup comparison are consistent with an attenuating PV–EI association at higher readiness. Nevertheless, no survey item directly measured marginal-return calculations, perceived scale constraints, or deliberate investment caution. Therefore, experience-based caution is only one possible mechanism, and future longitudinal or qualitative work is required to distinguish it from omitted financial or operational variables.

The predictive analysis reinforces that interpretation but also imposes an important discipline on the paper’s claims. The theory-informed linear benchmark that includes PV × TR outperforms the tuned XGBoost model on the untouched holdout sample. Greater algorithmic flexibility therefore does not improve prediction in this dataset. This negative result is substantively useful: it suggests that the dominant predictive structure is relatively parsimonious and that the theoretically specified interaction captures signal that a more flexible learner does not exploit more effectively. SHAP still identifies PV as the dominant feature and places TR second, but those attributions describe the fitted XGBoost model; they do not overturn the benchmark comparison or establish causality (Lundberg & Lee, 2017; Lundberg et al., 2020). The hybrid analysis consequently supports a more restrained conclusion than “machine learning performs better”: theory-driven structure is more predictive here, while XGBoost–SHAP is valuable as a diagnostic of feature contributions and possible nonlinear regularities.

The additional nested validation provides a more demanding check of the predictive comparison: the interaction-informed linear model retained a lower mean prediction error than the nested-tuned boosting alternatives. The defensible methodological insight is consequently a negative algorithmic-complexity result under the specified survey feature set, rather than an improvement attributable to boosting. Feature attribution from XGBoost remains a description of the fitted model and is not evidence that the less accurate algorithm should replace the benchmark. Wu et al. (2024) demonstrate explainable boosting in shrimp-price forecasting, while agricultural reviews identify variation in dataset coverage and validation as recurring issues (Kuan et al., 2025; Shawon et al., 2025). This study evaluates intention scores, so these application domains are not treated as directly equivalent.

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Theoretical and Methodological Contributions

The first contribution is decision-stage specificity. Prior research on shrimp farming has examined adoption of management practices, technology acceptance, adaptation choices, and willingness to invest (Joffre et al., 2019; Do & Ho, 2022; Ulhaq et al., 2022). This study isolates a later decision: whether an experienced user intends to increase the absolute area of HDPE-lined ponds. That distinction changes the theoretical problem because prior use supplies information about the technology while expansion creates a new marginal commitment. The study therefore separates adoption success from scale-up willingness and shows why a technology can be retained without being expanded.

The second contribution is a bounded extension of value-based reasoning to a production-investment context. Perceived value operates as an integrative assessment, but its antecedents are not restricted to conventional benefit and price constructs. Economic expectations, information from peer-oriented social media, external production threats, and perceived cost burden all enter the appraisal from different directions. The positive threat relationship is especially useful because it clarifies that external vulnerability and technology-related risk should not be collapsed into one risk construct. Their theoretical signs can differ because one increases the relevance of protection while the other increases sacrifice.

The third contribution concerns technological readiness. Most technology-adoption reasoning treats readiness or efficacy as enabling conditions. The reverse moderation observed here identifies a stage-dependent boundary: once users are experienced, greater capability may increase awareness of scale constraints and reduce reliance on a global value judgment. The result does not invalidate readiness as an enabling construct; it indicates that its role can change when the behavioral target shifts from adoption to expansion. Future models of agricultural technology scaling should therefore distinguish the capability to operate a system from the willingness to enlarge it.

The methodological contribution comes from treating explanation and prediction as separate empirical tasks rather than assuming that a strong structural model must also be the best predictor. Consistent with Shmueli (2010) and Shmueli et al. (2019), the study evaluates holdout performance against explicit benchmarks. The finding that XGBoost underperforms the theory-informed linear model is itself informative and avoids a common problem in hybrid SEM–machine-learning studies: presenting a complex algorithm as an improvement without demonstrating out-of-sample superiority. SHAP is consequently used as an interpretive layer for the trained learner, not as a substitute for structural inference.

The informatics-oriented contribution is an auditable comparison of constrained theory-informed features and a tuned nonlinear learner under common out-of-sample evaluations, with explicit separation between predictive ranking and model explanation. Such a comparison does not introduce a new algorithm, demonstrate a deployed decision system, or show that SHAP improves accuracy. The score-based nested analysis and the original SmartPLS structural estimation address different inferential tasks (Ringle et al., 2023; Legate et al., 2023). The importance of checking generalization, rather than assuming that complex learners always outperform simpler specifications, is also emphasized in recent agricultural machine-learning reviews (Jabed & Murad, 2024; Kuan et al., 2025).

Practical Implications

For extension agencies, cooperatives, lenders, and suppliers, the results imply that promoting expansion should focus on the economics and manageability of the next unit of HDPE area rather than repeating generic claims about the technology. Demonstrations should report operating costs, energy requirements, maintenance and liner-replacement needs, labor demands, and expected production outcomes on a comparable area basis. This would allow farmers to judge marginal value instead of extrapolating from a successful existing pond.

Support should also be segmented by technological readiness. Farmers with lower readiness may benefit from basic operating support that makes the value proposition credible and actionable. Farmers with higher readiness require a different intervention: evidence on scale management, workload, contingency capacity, working-capital requirements, and coordination across multiple ponds. For this group, additional technical training alone may have limited effect because the binding constraint may no longer be knowledge. Financial instruments that align repayment with production cycles, transparent estimates of recurrent costs, and access to rapid technical support may be more relevant to expansion decisions.

Because social-media influence contributes to perceived value, peer communication can be used as an extension channel, but the implication is not to maximize promotional exposure. Credible farm-level evidence, transparent reporting of failures as well as successes, and comparisons across production conditions are more likely to improve decision quality. Similarly, the positive role of climate and disease threats should not be used to frame HDPE as a universal protective solution. Communication should specify which vulnerabilities HDPE-based management can plausibly reduce and which risks remain outside the technology's control.

Limitations and Future Research

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The evidence is cross-sectional and concerns stated expansion intention, so the estimated relationships cannot establish temporal or causal effects and do not show that farmers subsequently increased HDPE area. A stronger design would follow households across production cycles and link baseline appraisals to verified changes in lined area, investment expenditure, survival, yield, and profitability. Panel data would also allow the proposed experience-based caution mechanism to be tested directly as farmers accumulate operating experience.

Because all predictors and intended expansion were reported by the same respondent in one survey, residual common-source and social-desirability effects remain possible despite the existing Harman and VIF diagnostics. The study cannot infer realized expansion or causal effects, and procedural safeguards not documented in the underlying collection records are not asserted.

External validity is constrained by the study area and sample composition. The survey covers post-merger Can Tho City and is weighted toward Soc Trang, while aquaculture conditions, infrastructure, credit access, salinity regimes, and market channels vary across the Mekong Delta. Replication in Ca Mau, Bac Lieu, Kien Giang, and other intensive shrimp areas would show whether the moderation pattern is context-specific or generalizable. Multi-group or hierarchical models could further examine whether expansion logic differs by farm size, HDPE share, years of use, production intensity, or financing source.

No households from the separate contemporary provincial jurisdictions of Ca Mau or Bac Lieu were included as an independent replication sample. The reported survey areas are the former Soc Trang, Can Tho, and Hau Giang administrative areas within post-merger Can Tho City. Because 189 of 356 respondents (53.1%) came from Soc Trang and the uploaded documentation does not establish probability-based sampling, neither population-representative regional inference nor extrapolation to all Vietnamese shrimp farmers is supported. A new regional survey is required for external replication; the present reanalysis cannot substitute for that study.

The measurement model is acceptable, but several indicators have moderate loadings and the climate-and-disease construct combines two related forms of production threat. Independent-sample validation should test whether those items remain stable and whether climate threat and disease threat are better represented as separate first-order constructs or as dimensions of a higher-order vulnerability construct. Future studies should also add objective or quasi-objective indicators actual operating cost, electricity use, realized survival, farm liquidity, debt exposure, and available pond area to reduce dependence on self-reported appraisal.

The available respondent-level analytic file consists of 28 five-category survey items and does not contain measured electricity consumption, actual operating costs, survival rates, or verified production accounts. Objective operational indicators therefore could not be added retrospectively. The indicators used here measure perceptions, not actual farm performance; follow-up data linkage will be needed to evaluate measurement against production records.

The predictive evidence should also be interpreted within the available sample and feature set. With 356 observations, a 107-case holdout, and six construct-score predictors, XGBoost has limited scope to reveal complex structure. Repeated nested cross-validation and external validation on a new regional sample would provide a more stable comparison. Future work could benchmark XGBoost against generalized additive models, random forests, CatBoost, and penalized regression while preserving a strict separation between training, tuning, and final evaluation. If nonlinear or threshold patterns recur across independent samples, they can then be translated into explicit hypotheses and tested in a new confirmatory design.

Finally, perceived value explains only part of its own variance, indicating that the expansion appraisal remains incomplete. Subsequent models should examine land availability, access to credit, realized production performance, shrimp price volatility, household labor, environmental regulation, and expectations about market demand. These variables are particularly relevant to the negative readiness moderation because they can distinguish whether technically capable farmers are more cautious because they recognize operational constraints, financial constraints, or diminishing returns to additional HDPE area.

CONCLUSION

This study explains intention to expand HDPE-lined shrimp ponds as a post-adoption investment decision rather than a continuation of initial technology acceptance. Among experienced users, perceived value is the central link between expected economic benefits, social-media information, production threats, financial burden, and further deployment. The results indicate that farmers expand when HDPE remains worthwhile at the margin, not simply because previous use has been favorable. Economic benefits raise that assessment, cost burden reduces it, and external threat and peer-oriented information add context to how value is formed.

The unexpected negative moderation by technological readiness provides the paper's most important boundary condition. Greater readiness does not make perceived value more influential; it weakens the value intention relationship. The evidence is consistent with the proposition that experienced and technically capable farmers apply a more constraint-sensitive test before scaling. The predictive analysis points in the same direction: the theory-informed linear model with the PV × TR interaction outperforms tuned XGBoost on the holdout sample. Complexity therefore adds interpretive detail through SHAP but does not deliver superior prediction in this dataset.

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