



Extension, Resources and Institutional Support Associated with Oil Palm Farmers' Adaptive Capacity in Riau, Indonesia

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HIGHLIGHTS

- Accessible and dialogical agricultural extension positively predicted the adaptive capacity of oil palm smallholders in Tapung, Riau, Indonesia.
- Household resources were the strongest predictor of adaptive capacity, with household income contributing far more than formal education.
- Private company support contributed more than government support to the institutional environment around farmers.
- Extension methods, household resources and institutional support jointly explained 37.3% of the variance in adaptive capacity among 203 oil palm farmers.

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ABSTRACT

Agricultural extension may strengthen farmers' responses to production, market and information change, but its contribution is rarely separated from supporting institutions. This cross-sectional study examined how extension methods, household resources and institutional support predicted adaptive capacity among oil palm farmers in three villages of Tapung Subdistrict, Indonesia, from December 2023 to April 2024. Of 214 farmers interviewed, 11 incomplete questionnaires were excluded and 203 complete cases were analysed using partial least squares structural equation modelling with 5,000 bootstrap samples, PLSpredict and the cross-validated predictive ability test. Extension methods ($\beta=0.106$; $p=0.016$) and household resources ($\beta=0.492$; $p<0.001$) positively predicted adaptive capacity. Institutional support was positive ($\beta=0.151$; $p=0.032$), but its bias-corrected interval included zero; therefore, H3 was inconclusive. Separating the resource construct showed that household income carried the association ($\beta=0.483$; $p<0.001$), whereas formal education did not ($\beta=0.022$; $p=0.764$). The model explained 37.3% of adaptive-capacity variance. All indicator-level Q^2 predict values were positive, and PLS-SEM outperformed the linear benchmark for four of six indicators. The findings suggest combining accessible, dialogical extension with financially feasible recommendations, while coordinated public-private support requires further testing.

INTRODUCTION

Indonesia's oil palm sector supports rural livelihoods, and smallholders manage a substantial share of the planted area (BPS-

Statistics Indonesia, 2023). Riau Province is the country's largest oil palm producing region, yet smallholders operate amid climate variability, volatile prices, productivity gaps and changing

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sustainability requirements (Novira, 2023; Paterson, 2023; Reich et al., 2025). Adjustment depends on the information farmers receive, on household liquidity and on the advisory services within reach (Maguire-Rajpaul et al., 2020; Ogundeji et al., 2022).

Adaptive capacity is the set of resources, skills and institutional relations that allow a farm household to anticipate change, absorb its effects and reorganise its practices (Manevska-Tasevska et al., 2021; Bartelet et al., 2023). Resources, learning and surrounding institutions shape it together. Education and income improve farmers' ability to interpret information and absorb adjustment costs, while information access and institutional connections widen the range of responses available (Maguire-Rajpaul et al., 2020; Atube et al., 2021; Ogundeji et al., 2022; Yadav and Ghosh, 2023). Where advice is unreachable or detached from the decisions farmers face, those resources stay unused.

Participatory and farmer field school approaches strengthen farmers' innovativeness and enable locally relevant decisions (van den Berg et al., 2020; Osumba et al., 2021; Dosso et al., 2023; Nain et al., 2024). Digital and conventional channels raise knowledge when they stay accessible and tied to farmers' circumstances (Antwi-Agyei & Stringer, 2021; Niranjana et al., 2023; Murya et al., 2026). Where public advisory capacity is limited relative to the farming population, private companies and government programmes together form a pluralistic extension environment (Kamruzzaman et al., 2021; Godara et al., 2024a; Godara et al., 2024b). In oil palm the two are entangled: scheme farmers are advised through their company contract, while independent growers depend on public services (Sibhatu et al., 2025). The present analysis keeps them apart. Extension methods denote the accessibility, dialogical quality and participatory design of advisory delivery (Dosso et al., 2023); institutional support denotes the organisational resources companies and public agencies supply to sustain those processes (Kangogo et al., 2020; Kamruzzaman et al., 2021). Studies that merge the two cannot show whether adaptive capacity follows from the quality of communication or from the institutions behind it, so extension managers have no clear target.

Much adaptive capacity research remains descriptive, profiling farmers socioeconomically or sorting them into low, medium and high categories (Vijayabhinnandana et al., 2022; Sthitaprajna and Shasani, 2026). Such work identifies education, information use and extension participation as correlates of adaptation, but says little about the mechanisms an extension organisation can change, and the joint effect of extension methods and institutional partnerships is still untested among oil palm smallholders. Separating the two constructs identifies where extension managers should invest, and out-of-sample assessment tests whether the relationships hold beyond the sample (Shmueli et al., 2019; Liengaard et al., 2021). This study tests three hypotheses: extension methods positively influence adaptive capacity (H1); farmer household resources positively influence adaptive capacity (H2); and institutional support positively influences adaptive capacity (H3).

METHODOLOGY

A cross-sectional survey was conducted from December 2023 to April 2024 in Petapahan, Sari Galuh and Kenantan villages, Tapung Subdistrict, Kampar Regency, Riau Province. The villages

were selected purposively because oil palm was an important livelihood. The reference population comprised 188,694 oil palm-farming households in Kampar Regency. Slovin's formula with a 7% tolerance yielded approximately 203. Without a complete village sampling frame, accessible farmers who actively managed oil palm farms were recruited by convenience sampling. Of 214 farmers interviewed to allow for incomplete questionnaires, 11 incomplete records were excluded, leaving 203 cases. The non-probability design limited statistical generalisation beyond the analysed sample.

Structured interviews used indicators adapted from studies of advisory delivery, institutional support and adaptive capacity (Maguire-Rajpaul et al., 2020; Dosso et al., 2023; Manevska-Tasevska et al., 2021). The questionnaire was pilot-tested with 15 oil palm farmers from neighbouring villages who were excluded from the main sample. The pilot assessed clarity, wording, response suitability and contextual relevance; ambiguous items were revised before enumerator training. Items used four-point scales from 1 (very low/never) to 4 (very high/always); education was coded 1–5 and monthly income in rupiah. Fourteen respondents did not report income. The missing-data mechanism was not formally tested; median imputation was used pragmatically because income was right-skewed.

Adaptive capacity was reflective, with six indicators covering technical, business, networking and digital-information responses. Extension methods combined information accessibility, dialogue and participation. Household resources combined education as human capital for interpreting information and income as financial capacity for funding adjustments; institutional support combined company and government support. Of 22 initial indicators, nine were removed when weights were non-significant and loadings below 0.50, or over 85% of responses occupied one category. Conceptual coverage was re-checked, leaving 13 indicators.

PLS-SEM was estimated in SmartPLS 4 (Ringle et al., 2024) using path weighting and 5,000 two-tailed percentile-bootstrap resamples, with bias-corrected intervals as sensitivity checks (Hair et al., 2022). For full-collinearity assessment, each construct was regressed on all remaining constructs in turn; all VIFs were below 3.3 and were evaluated separately from routine inner-model VIFs (Kock, 2015). PLSpredict (Shmueli et al., 2019) and CVPAT (Liengaard et al., 2021) used 10 folds and 10 repetitions.

RESULTS

Measurement quality

Adaptive capacity met the requirements for internal consistency and convergent validity. Cronbach's alpha was 0.803, rho A was 0.827, composite reliability was 0.859 and average variance extracted was 0.507. All six loadings were positive and significant. Three loadings fell below 0.708. They were retained because their removal would not have raised composite reliability or average variance extracted, both of which already met their thresholds, and because they carried distinct business capacity content (Hair et al., 2022). Indicator VIF values ranged from 1.298 to 1.875, indicating no critical collinearity (Table 1).

The formative composites also satisfied the assessment criteria. All formative indicators had VIF values below 1.13.

Table 1. Reflective measurement of adaptive capacity

Indicator	Loading	t-value	p-value	VIF
Farm-scale development	0.615	12.563	<0.001	1.334
Livelihood diversification	0.591	9.001	<0.001	1.298
Digital information use	0.707	16.043	<0.001	1.479
External cooperation	0.734	22.124	<0.001	1.650
Manual weed management	0.780	23.007	<0.001	1.875
Refugia-based pest control	0.816	33.545	<0.001	1.797

Source: Primary survey (2024), SmartPLS 4 output. Note: VIF=variance inflation factor; AVE=average variance extracted. Reliability: Cronbach's alpha=0.803; rho_A=0.827; composite reliability=0.859; AVE=0.507; n=203. Refugia-based pest control refers to flowering border plantings that shelter the natural enemies of pests.

Information accessibility and dialogical communication made significant relative contributions to extension methods. Participation-building had a non-significant weight but a significant absolute loading of 0.590 and was retained to preserve the participatory component. Income dominated household resources; education had a weak relative contribution but a significant absolute loading and was retained for conceptual coverage. Both company and government support contributed significantly to institutional support (Table 2).

Structural relationships and predictive validity

The predictors jointly explained 37.3% of adaptive-capacity variance (adjusted $R^2=0.364$; Table 3). Household resources had the largest coefficient and a medium effect size. Extension methods had a positive coefficient but negligible effect size ($f^2=0.017$). H1 and H2 were supported by p-values and both confidence-interval procedures. Institutional support was positive and met the pre-specified percentile-bootstrap criterion for H3, but its bias-corrected lower bound marginally included zero; H3 is therefore reported as

inconclusive. Routine inner-model VIF values of 1.033 to 1.370 indicated no critical predictor collinearity. Separately, full-collinearity VIF values below 3.3 provided no strong indication of common method bias. The standardised root mean square residual (SRMR) was 0.067. Three robustness checks were run. Entering household income and formal education as separate single-item predictors left income strongly significant ($\beta=0.483$; $p<0.001$) and education not ($\beta=0.022$; $p=0.764$), with explained variance unchanged at 37.4%. Removing the two agronomic indicators from adaptive capacity strengthened extension methods ($\beta=0.143$; $p=0.015$) but left institutional support non-significant ($\beta=0.096$; $p=0.225$) and weakened internal consistency ($\alpha=0.676$). Removing digital information use held extension methods steady ($\beta=0.115$; $p=0.014$) and made institutional support significant under both interval procedures ($\beta=0.189$; $p=0.009$). The extension and income relationships hold throughout; the institutional-support path moves with the specification.

All six adaptive-capacity indicators had Q^2 predict values above zero. PLS-SEM produced lower root mean squared error (RMSE)

Table 2. Formative composite assessment

Construct	Indicator	Weight	p(weight)	Loading	p/loading)	VIF
Extension methods	Information accessibility	0.563	0.009	0.674	<0.001	1.026
	Dialogical communication	0.575	0.023	0.736	<0.001	1.104
	Participation-building	0.334	0.233	0.590	0.007	1.116
Household resources	Formal education	0.073	0.549	0.395	<0.001	1.123
	Household income	0.974	<0.001	0.998	<0.001	1.123
Institutional support	Private-company support	0.799	<0.001	0.883	<0.001	1.032
	Government support	0.476	0.005	0.617	<0.001	1.032

Source: Primary survey (2024), SmartPLS 4 bootstrap output. Note: VIF=variance inflation factor. Non-significant weights were retained only when their absolute loadings were significant and conceptual coverage would otherwise be reduced. Of the nine indicators removed during specification, three belonged to extension methods (material relevance, practical-material clarity, multi-party communication), two to institutional support (farmer-group support, university support) and four to the resource construct (non-formal training, farming experience, farmer-group participation, age). Near-uniform response shares were 94.1% for farmer group membership and 86.2% for training attendance; the removal rule is given in the methodology.

Table 3. Structural model for adaptive capacity

Hyp.	Relationship	β	t	p	Percentile 95% CI	BCa 95% CI	f^2
H1	Extension methods → Adaptive capacity	0.106	2.417	0.016	[0.026, 0.198]	[0.016, 0.188]	0.017
H2	Household resources → Adaptive capacity	0.492	6.480	<0.001	[0.340, 0.635]	[0.329, 0.626]	0.282
H3	Institutional support → Adaptive capacity	0.151	2.151	0.032	[0.020, 0.297]	[-0.0004, 0.277]	0.027

Source: Primary survey (2024), SmartPLS 4 bootstrap output. Note: Hypothesis decisions used the two-tailed percentile interval; BCa=bias-corrected and accelerated confidence interval. H3 met the percentile criterion but is reported as inconclusive because the BCa interval included zero. $R^2=0.373$; adjusted $R^2=0.364$; SRMR=standardised root mean square residual=0.067; n=203.

Table 4. Out-of-sample prediction of adaptive capacity

Indicator	Q ² predict	PLS RMSE	LM RMSE	PLS MAE	LM MAE	Lower error
Farm-scale development	0.121	0.510	0.516	0.358	0.359	PLS
Livelihood diversification	0.065	0.737	0.742	0.567	0.572	PLS
Digital information use	0.144	0.523	0.528	0.425	0.434	PLS
External cooperation	0.186	0.486	0.488	0.378	0.387	PLS
Manual weed management	0.183	0.496	0.491	0.398	0.396	LM
Refugia-based pest control	0.299	0.509	0.505	0.389	0.366	LM

Source: Primary survey (2024), SmartPLS 4 PLSpredict output. *Note:* PLS=partial least squares; LM=linear model; RMSE=root mean squared error; MAE=mean absolute error; Q²predict=predictive relevance; CVPAT=cross-validated predictive ability test. Construct Q²predict=0.332. CVPAT: PLS vs indicator average, loss difference=-0.057, $p < 0.001$; PLS vs LM, difference=-0.002, $p = 0.685$.

and mean absolute error (MAE) than the linear-model benchmark for four indicators, indicating medium predictive power. At construct level, Q²predict was 0.332 (Table 4). CVPAT showed significantly lower prediction loss than the indicator-average benchmark, whereas the small advantage over the linear model was not statistically significant.

DISCUSSION

Household resources show the strongest association with adaptive capacity, and the formative weights place almost all of that association on household income. Income lets farmers absorb adjustment costs and carry short-term risk. Education helps them read new information but does not supply the same financial room to act on it. The construct is therefore best read as a measure of household income. This reading fits evidence that education, income and information use shape adaptation among farmers (Maguire-Rajpaul et al., 2020; Atube et al., 2021; Yadav and Ghosh, 2023; Sthitaprajna & Shasani, 2026). The programme implication is differentiation: farmers with little liquidity need practical, low-cost recommendations and a route to finance.

Extension methods have a positive but small effect. Accessibility and dialogue carry the strongest relative weights, and participation keeps a substantial absolute loading. Extension therefore works through exchange between adviser and farmer. Accessible advice cuts the cost of searching for information, and dialogue ties technical content to the conditions of a particular farm. Participation then lets farmers try a recommendation and adjust it. Osumba et al. (2021); Dosso et al. (2023) and Maurya et al. (2026) report the same mechanisms where participatory approaches and digital advisory systems are in place. Extension operates on farmers' decision capacity, and the small effect size ($f^2 = 0.017$) reflects that limit: farmers who decide to adjust can act only within the resources at hand. Extension packages work best when accessible, dialogical communication comes with recommendations farmers can afford to follow. Removing the agronomic practice indicators raises that coefficient, locating extension's contribution in the informational, networking and business dimensions of adaptive capacity.

Institutional support is formed by company and government contributions, with company support carrying the greater relative weight. Sitting close to the farm in the value chain, companies pass technical advice and market information to farmers through the commercial relationship. Government support carries a broader mandate and reaches any single commodity less intensively. These weights describe contribution to the composite and imply no

ranking of institutional performance. H3 is inconclusive, so institutional support is best treated as a plausible enabling factor awaiting a better-powered test. Most respondents farmed independently, only 22.2% holding a company scheme contract, so company support here reflects advisory and market contact reaching farmers outside contractual plasma arrangements. The two roles should therefore be coordinated: companies can supply specialised, value-chain-linked assistance, while public agencies stay responsible for minimum service standards, the neutrality of advice, and farmers outside company schemes (Kangogo et al., 2020; Ma & Rahut, 2024; Shitu et al., 2026).

The model combines moderate explanatory power with positive out-of-sample relevance, although CVPAT showed no significant advantage over the linear benchmark, so the predictive claim is a modest one. Communication quality operates within the limits set by farmers' material resources and the institutions they can reach. Five limits qualify these results. The cross-sectional design cannot establish causal direction, and reverse causation is most plausible on the income path. Purposive site selection and convenience recruitment prevent statistical generalisation to all oil palm farmers in Kampar Regency. The household-resource composite is dominated by income. Two adaptive-capacity indicators record what farmers do, while the construct is defined as what they are able to do, and manual weeding may partly reflect limited purchasing power for herbicide among independent growers (Sibhatu et al., 2025). The missing-data mechanism for 14 imputed income values was not formally tested, and the pilot test involved only 15 farmers from neighbouring villages. Adding access to finance and farm assets, and following farmers over time, would address the causal direction and the narrow resource measure.

CONCLUSION

Accessible, dialogical and participatory agricultural extension contributes to oil palm farmers' adaptive capacity, though it explains less of that capacity than household income does. Company and government support may provide an enabling institutional foundation, but that relationship shifts with how adaptive capacity is measured and cannot yet be treated as established. Affordability should be considered when extension recommendations are designed, and whether screening for it improves uptake is a question for future intervention studies. Whether linking advisory contact to credit and market information raises adaptive capacity was not tested here and merits direct evaluation. Because extension relates more closely to the informational, networking and business dimensions of

adaptive capacity than to specific field practices, public and company services should each take a different part of that work.

DECLARATIONS

Research ethics statement: Participation in this study was voluntary. All respondents received written and verbal information about the purpose of the study, the voluntary nature of participation and their right to withdraw at any stage, and informed consent was obtained from every respondent before the interview. No identifying information was recorded, respondent identities were anonymised throughout data processing and reporting, and the data were used exclusively for the research purposes described. The study was carried out under IPB University research Decree No. 483/IT3.D10/PT.01.03/P/B/2023. The signed IJEE Research Ethics Statement, in the prescribed format, accompanies this submission.

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