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From Internal Readiness to Technology Adoption: Innovation Capability and Knowledge Sharing among Smallholder Farmers

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Abstract

The availability of agricultural technologies does not necessarily lead smallholder farmers to adopt them. Before using a new practice, farmers need to judge whether the information is reliable, whether the practice fits their land and labor conditions, and whether the expected benefits are sufficient to justify the costs and risks of trial and adjustment. Drawing on an internal readiness perspective, this study examines how human capital and psychological capital are associated with technology adoption through innovation capability, and whether knowledge sharing changes the relationship between innovation capability and technology adoption. Survey data from 408 smallholder households in Henan Province, China, were analyzed using partial least squares structural equation modeling. The results show that human capital is positively associated with both innovation capability and technology adoption. Psychological capital is positively associated with innovation capability, but its direct relationship with technology adoption is not significant. Innovation capability mediates the relationships between human capital, psychological capital, and technology adoption. Knowledge sharing has a weak positive lower-order association with technology adoption, while its interaction with innovation capability is negative and significant. This negative interaction should not be interpreted as evidence that knowledge sharing is harmful. Rather, when information is abundant and heterogeneous, farmers with stronger innovation capability may need to compare sources, screen inconsistent advice, and verify local applicability before taking action. The findings suggest that smallholder technology adoption depends on internal resources, capability enactment, and the conditions under which shared knowledge is interpreted. Agricultural extension should therefore combine technology dissemination with support for farmers' diagnostic, adaptive, and information-verification skills.

Keywords: smallholder farmers, technology adoption, internal readiness, human capital, psychological capital, innovation capability, knowledge sharing, rural China

1. Introduction

For smallholder farmers, the adoption process often begins before a new practice is first used in the field. At this stage, farmers assess information credibility, compatibility with land and labor conditions, and whether expected gains can justify the costs and risks of trial and adjustment (Feder et al., 1985; Pannell et al., 2006; Kuehne et al., 2017). Accordingly, access to technology alone does not explain farmers' adoption decisions. Adoption is also a process through which farmers interpret information, assess practical feasibility, and adapt new practices to local production conditions (Rogers, 2003; Meijer et al., 2015).

Recent studies show that farmers' adoption of improved agricultural practices is shaped by multiple individual, informational, institutional, and service-related factors, including education, farming experience, access to information, perceived usefulness, extension and advisory support, risk exposure, and access to digital services (Ruzzante et al., 2021; Arslan et al., 2022; Porciello et al., 2022; Mao et al., 2024; Tao et al., 2024). Nevertheless, these factors do not fully explain why farmers facing similar production opportunities often behave differently. Some farmers can interpret new information, test a practice, and incorporate it into routine production, whereas others remain hesitant or fail to move from awareness to use.

This difference highlights farmers' internal readiness. In this study, internal readiness is represented by two distinct resources: human capital and psychological capital. Human capital refers to farming knowledge, technical understanding, accumulated experience, and practical problem-solving competence, which are repeatedly identified as relevant to agricultural technology adoption (Ruzzante et al., 2021; Arslan et al., 2022; Manzoor et al., 2025). Psychological capital refers to confidence, hope, optimism, and resilience in uncertain farming situations (Luthans et al., 2007; Avey et al., 2011). Both may support technology adoption, but they are unlikely to operate in the same way. Human capital is closer to technical understanding and implementation, while psychological capital is closer to persistence, confidence, and willingness to keep learning.

Internal resources alone, however, do not guarantee adoption. The Resource-Based View explains why actors differ in their intangible resources, but Dynamic Capabilities Theory emphasizes that resources become useful only when they are mobilized, recombined, and adapted to changing conditions (Barney, 1991; Teece et al., 1997; Teece, 2007). In the smallholder context, knowledge, experience, and confidence must be translated into an ability to search for information, evaluate alternatives, experiment with improved practices, and adapt them locally. This study treats innovation capability as the mechanism through which internal readiness is put into use.

Knowledge sharing also shapes the conditions under which farmers interpret and apply new agricultural knowledge. In rural agricultural settings, smallholders acquire technical guidance from a broad range of sources, including kinship and peer networks, farmer cooperatives, model farmers, agricultural extension personnel, and professional service providers, as well as rapidly developing digital channels. These knowledge interactions may reduce perceived technological uncertainty and help farmers develop a more contextual understanding of new practices. Recent studies suggest that peer learning, extension support, cooperative participation, and farmer interaction networks are related to the progress and outcomes of agricultural technology adoption (Izadi et al., 2024; Manda et al., 2024; Park, 2025; Tumwebaze et al., 2025). Even so, externally acquired knowledge is often uneven and sometimes inconsistent across sources. Farmers must therefore compare, filter, and verify heterogeneous technical information before implementing new technologies in actual production.

Using survey data from 408 crop-farming households in Henan Province, China, this study examines the direct and indirect associations among human capital, psychological capital, and agricultural technology adoption, with innovation capability as the mediating mechanism. This study further investigates the moderating role of knowledge sharing in the relationship between innovation capability and farmers' adoption decisions. The analysis contributes to the literature in three ways. It first distinguishes the technical-competence side of internal readiness from its psychological-agency side. It then explains innovation capability as the pathway through which internal resources are enacted in adoption-related behavior. Finally, it clarifies why knowledge sharing may be positively related to adoption overall while weakening the immediate innovation capability–adoption relationship when farmers must evaluate inconsistent external information.

2. Literature Review and Hypothesis Development

2.1 Internal Readiness and Capability Enactment

Technology adoption among smallholder farmers can be better understood as a contextual and gradual process rather than a one-off decision. Before integrating new farming techniques into routine production, farmers usually make practical judgments about whether a new practice can work under their own production conditions. They assess the compatibility of innovative practices with their land conditions, crop varieties, labor endowments, financial status, and existing production arrangements, and further evaluate whether the anticipated benefits can justify the costs and risks of trial adoption. In this regard, technology adoption is not confined to mere exposure. Instead, incorporating new practices into routine farming operations entails continuous cognitive learning, feasibility assessment, field experimentation, and local adjustment (Feder et al., 1985; Pannell et al., 2006; Rogers, 2003; Kuehne et al., 2017).

This interpretation is consistent with evidence from agricultural adoption research. Existing meta-analytic studies show that farmers' education, household resource endowments, credit access, land scale, extension service participation, and organizational involvement are associated with technology adoption outcomes, though the magnitude and significance of these associations vary across technological types and situational contexts (Ruzzante et al., 2021; Arslan et al., 2022). Such variation across contexts indicates that external technology availability alone does not fully explain differences in adoption behavior. Even with identical external conditions, farmers may make distinct adoption decisions due to differences in knowledge accumulation, practical experience, psychological traits, and the ability to interpret and use information.

This study adopts the construct of internal readiness to explain such individual-level heterogeneity among smallholders. The emphasis on internal readiness does not deny the role of external support. Rather, it suggests that external opportunities are more likely to matter when farmers have the knowledge, confidence, and adaptive capacity needed to interpret and use them. Dynamic capabilities theory is useful for this argument because it focuses on how resources are mobilized and adapted rather than static resource possession (Teece et al., 1997; Teece, 2007). In the context of smallholder agriculture, farmer innovation capability differs from formal research and development activities. It refers to the practical capacity to identify useful agricultural information, compare alternative technical options, implement field trials, and revise practices to fit local production conditions (Cohen & Levinthal, 1990; Teece, 2007; Jalotjot & Tokuda, 2024).

2.2 Human Capital, Innovation Capability, and Technology Adoption

Human capital encompasses the knowledge, operational skills, production experience, and practical judgment that guide farmers' production and technological decision-making (Ruzzante et al., 2021; Arslan et al., 2022; Manzoor et al., 2025). Within smallholder farming contexts, human capital cannot be reduced to formal education alone. Formal schooling may improve farmers' information-processing ability, but experiential knowledge and context-specific judgment are also important, particularly when farmers face practical problems during technology implementation.

Human capital is expected to be positively associated with farmers' innovation capability. Farmers with broader knowledge and richer farming experience are better positioned to identify useful agricultural information, assess its relevance to local production conditions, recognize potential implementation barriers, and refine practices through trial and adjustment. Recent digital agriculture research also suggests that education, knowledge, and technical skills are closely related to farmers' ability to use agricultural technology tools (Manzoor et al., 2025).

Human capital may also be directly associated with technology adoption. Farmers with a better understanding of new agricultural practices may be able to evaluate their practical applicability, input costs, potential risks, and operational requirements more carefully. Such understanding may help farmers avoid inappropriate implementation and make adoption more feasible. A body of prior agricultural adoption research also recognizes farmers' educational attainment and individual competency as important correlates of agricultural technology use (Ruzzante et al., 2021; Arslan et al., 2022; Zhang et al., 2024).

H1: Human capital is positively associated with innovation capability.

H2: Human capital is positively associated with technology adoption.

2.3 Psychological Capital, Innovation Capability, and Technology Adoption

Psychological capital constitutes a set of positive psychological resources, covering self-efficacy, hope, optimism, and resilience (Luthans et al., 2007; Avey et al., 2011). These resources are relevant to agricultural technology adoption, as the uptake of new farming techniques generally entails deferred benefits, ongoing learning demands, adaptive adjustment costs, and potential early-stage implementation setbacks.

Psychological capital is expected to be positively related to farmers' innovation capability. Self-efficacy and resilience may support information searching and continued learning when farmers face uncertain early outcomes. Hope and optimism may also help farmers remain engaged during technological trials and adaptive adjustments. Together, these psychological resources can support exploratory learning and adaptive problem-solving in routine agricultural production. Recent agricultural innovation studies also suggest that psychological factors are associated with whether farmers progress from awareness to adoption (Chindasombatcharoen et al., 2024).

The direct relationship between psychological capital and adoption is plausible but less straightforward. Positive psychological traits may encourage experimentation, but they do not guarantee technical understanding, access to credible information, or favorable implementation conditions. For smallholder farmers, technology adoption decisions are also subject to perceived implementation burden, external facilitating conditions, trust levels, operational constraints, and individual adoption willingness (Zhang et al., 2024). As such, psychological capital may be linked to technology adoption both directly and indirectly through innovation capability.

H3: Psychological capital is positively associated with innovation capability.

H4: Psychological capital is positively associated with technology adoption.

2.4 Innovation Capability as a Mediating Mechanism

Innovation capability characterizes farmers' practical capacity to identify useful agricultural information, absorb relevant knowledge, evaluate alternative production schemes, conduct small-scale trials, and adapt improved practices to local farming conditions (Cohen &

Levinthal, 1990; Teece et al., 1997; Teece, 2007; Jalotjot & Tokuda, 2024). In practice, smallholder farmers rarely implement introduced agricultural technologies in their original form. Instead, farmers routinely adjust planting schedules, input levels, field management routines, machinery application patterns, and collaborative arrangements with agricultural service providers. Such adaptive behaviors are particularly essential for complex agricultural technologies, which typically comprise multiple interrelated operational practices rather than standalone technical inputs (Hörner et al., 2022).

On this basis, this study posits that innovation capability mediates the association between human capital and agricultural technology adoption. Human capital, represented by knowledge and experience, does not necessarily lead to adoption on its own; its role may also depend on farmers' ability to search for information, assess applicability, conduct field trials, and adapt techniques locally (Teece, 2007; Manzoor et al., 2025; Jalotjot & Tokuda, 2024). A similar mechanism may apply to psychological capital. Farmers' confidence and perseverance are more likely to be related to adoption when these psychological attributes are translated into persistent learning, small-scale experimentation, and practical problem-solving in routine agricultural production (Luthans et al., 2007; Avey et al., 2011; Chindasombatcharoen et al., 2024).

H5: Innovation capability is positively associated with technology adoption.

H6: Innovation capability mediates the relationship between human capital and technology adoption.

H7: Innovation capability mediates the relationship between psychological capital and technology adoption.

2.5 Knowledge Sharing as a Boundary Condition

Knowledge sharing refers to the exchange, receipt, and interpretation of agricultural information, technical advice, and on-farm experience through interpersonal, organizational, and digital channels (Argote & Ingram, 2000; Szulanski, 1996; Izadi et al., 2024; Tumwebaze et al., 2025). In this study, knowledge sharing is treated primarily as a contextual boundary condition rather than as an independent direct-effect hypothesis. It is expected to alter how innovation capability is associated with technology adoption. Consistent with standard PLS-SEM interaction testing procedures, the direct path from knowledge sharing to technology adoption is retained as the required lower-order main effect in the interaction model (Hair et al., 2022; Sarstedt et al., 2022).

The role of knowledge sharing is conditional. Active knowledge exchange can improve access to experience-based technical information, but intensive incoming information may also increase the need for comparison, screening, and validation. Research on rural knowledge networks and agricultural knowledge management suggests that farmer interactions shape how practical knowledge circulates and how farmers interpret adoption opportunities (Izadi et al., 2024; Park, 2025; Tumwebaze et al., 2025).

Under lower levels of knowledge sharing, farmers may rely more directly on their own innovation capability to evaluate and implement new agricultural technologies. At higher levels of knowledge sharing, farmers with stronger innovation capability may first use it to screen, compare, and validate diverse or even contradictory external advice before making adoption decisions. Intensive knowledge inflows may increase the cognitive and practical verification burden, making the innovation capability–adoption relationship less immediate (Argote & Ingram, 2000; Szulanski, 1996; Park, 2025).

H8: Knowledge sharing moderates the relationship between innovation capability and technology adoption, such that the positive relationship weakens under higher levels of knowledge sharing.

2.6 Conceptual Framework

Figure 1 presents the conceptual framework. Human capital and psychological capital represent internal readiness, innovation capability represents capability enactment, and technology adoption represents the behavioral outcome. Knowledge sharing is positioned as a boundary condition of the innovation capability–technology adoption relationship, with its lower-order path retained for moderation estimation.

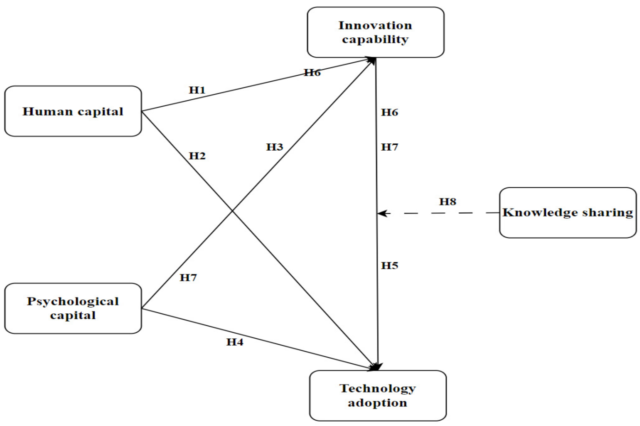

Figure 1. Conceptual framework of the study

Note(s): HC = human capital; PC = psychological capital; IC = innovation capability; KS = knowledge sharing; TA = technology adoption. Solid lines show the hypothesized direct and mediating relationships; the dashed line shows the lower-order KS–TA relationship; and the dotted line shows the moderating effect of KS. H6 and H7 refer to the indirect effects through IC.

3. Methodology

3.1 Research Setting and Survey Design

This study used a cross-sectional, interviewer-assisted household survey of smallholder crop-farming households in Henan Province, China. The farm household was used as the unit of analysis because decisions about technology use, input purchases, labor allocation, and production adjustments are typically made within the household production unit.

Henan is a suitable setting for examining the proposed relationships. Crop farming remains important in the province, and smallholder households differ in production experience, learning capacity, and access to locally usable agricultural information. These differences allow examination of whether internal readiness and knowledge-use conditions are associated with technology adoption in a major agricultural province. The aim is not to treat Henan as representative of all farming systems, but to use this context to test relationships that are theoretically relevant to smallholder technology adoption.

Data were collected through an interviewer-assisted questionnaire survey because rural respondents differed in education level and familiarity with scale-based survey items. This approach was used to improve item comprehension while keeping responses grounded in respondents' own farming experience. All field investigators received the same training before data collection and were allowed to clarify item meanings when necessary.

To reduce interviewer influence, interviewers were instructed not to provide suggestive information or guide respondents' choices. This procedure was intended to reduce invalid and incomplete responses and to keep responses grounded in participants' own farming experiences and independent judgments.

3.2 Sampling Procedure and Retained Sample

Following data cleaning and screening, 408 valid questionnaires were retained for analysis. Tables 1 and 2 summarize the demographic and production-related characteristics of the final sample. These descriptive indicators are reported to clarify the study's empirical context.

Table 1. Demographic profile of respondents (n = 408)

Characteristic	Category	n	%
Gender	Male	236	57.84
	Female	172	42.16
Age group	25-34 years	21	5.15
	35-44 years	140	34.31
	45-54 years	192	47.06
	55-64 years	49	12.01
	65-74 years	4	0.98
	75 years and above	2	0.49
Family education level	Primary education or below	49	12.01
	Lower secondary education	219	53.68
	Upper secondary education	119	29.17
	College diploma or above	21	5.15
Respondent's education level	Non-literate	4	0.98
	Primary education	127	31.13
	Lower secondary education	215	52.70
	Upper secondary education	53	12.99
	College diploma or above	9	2.21
Marital status	Single	4	0.98
	Married	388	95.10
	Divorced	8	1.96
	Widowed	8	1.96
Cooperative membership	Yes	182	44.61
	No	226	55.39
Household health status	Very poor	1	0.25
	Poor	9	2.21
	Fair	89	21.81
	Good	193	47.30
	Very good	116	28.43
Respondent's personal health status	Poor	8	1.96
	Fair	96	23.53
	Good	168	41.18
	Very good	136	33.33

Note(s): Percentages are calculated based on the retained valid sample of 408 respondents.

The retained sample was composed mainly of middle-aged farmers, with most respondents aged 35-54. Lower secondary education was the most frequently reported level of education, and 44.61% of respondents were members of cooperatives. This profile is broadly consistent with the characteristics of experienced smallholder crop-farming households.

Table 2. Household and farm characteristics (n = 408)

Variable	Mean	SD	Min	Max
Household size	5.18	1.24	2	11
Years of farming experience	19.92	6.52	5	30
Cultivated land area (mu)	8.40	5.24	2.50	40

Note(s): One mu equals approximately 0.067 hectares.

3.3 Measures

All latent constructs were operationalized using reflective measurement items on a five-point

Likert scale, anchored from 1 (strongly disagree) to 5 (strongly agree). The measurement scheme was aligned with the theoretical role of each construct in the model. Specifically, the human capital construct reflects farmers' agricultural knowledge, practical operational skills, experiential judgment, and field problem-solving capacity. Psychological capital captured confidence, hope, optimism, and resilience. Innovation capability captured information search, alternative comparison, small-scale experimentation, and local adaptation. Technology adoption captured actual use, continued use, routinization, and willingness to expand effective practices. Knowledge sharing captured peer exchange, willingness to share, advice seeking, and learning from shared knowledge.

The items were adapted from research on agricultural technology adoption, psychological capital, dynamic capabilities, innovation capability, and knowledge sharing, and were then contextualized to smallholder crop-farming production. The full measurement items and source references are reported in Appendix A. Table 3 reports the operational definitions used in the study.

Table 3. Operational definitions of constructs

Construct	Operational definition in this study	Illustrative item focus
Human capital (HC)	Farm household knowledge, production experience, technical understanding, and practical competence relevant to crop production and technology use.	Understanding, judging, and applying improved farming methods
Psychological capital (PC)	Positive psychological resources of the main farming decision-maker, including confidence, hope, optimism, and resilience in farming tasks.	Confidence and persistence under uncertain production conditions
Innovation capability (IC)	Household ability to search for useful information, evaluate alternatives, experiment with improved practices, and adapt them to local production conditions.	Learning, experimentation, adaptation, and problem-solving
Technology adoption (TA)	Actual and continued use of improved farming practices, including routinized implementation and willingness to expand effective practices.	Use, continued use, routinization, and expansion intention
Knowledge sharing (KS)	Exchange, receipt, and learning-oriented use of agricultural information, advice, and practical experience through local or external channels.	Sharing, receiving, and applying farming knowledge

3.4 Data Analysis

Partial least squares structural equation modeling (PLS-SEM) was used because the model includes multiple reflective constructs, mediation paths, and a moderation path, and because the analysis focuses on explanation and prediction. The measurement model was assessed using indicator loadings, Cronbach's alpha, rho_a, composite reliability, average variance extracted, and the heterotrait-monotrait ratio. The structural model was assessed using standardized path coefficients, bootstrapping, R^2, adjusted R^2, f^2, VIF, indirect effects, and simple slopes. Predictive performance was further examined using PLSpredict and CVPAT (Hair et al., 2022; Henseler et al., 2015; Shmueli et al., 2019; Liengaard et al., 2021).

3.5 Bias Controls and Sensitivity Checks

Several steps were taken during data collection to reduce the risk of common-method bias. Respondents completed the survey anonymously, and the items were written as clearly as possible to avoid unnecessary ambiguity. During the fieldwork, interviewers were asked to keep their explanations neutral and not to influence respondents' choices. Items related to predictors and outcomes were also placed in separate sections of the questionnaire. After data collection, Harman's single-factor test and inner-model VIFs were used as statistical checks for possible common method bias (Podsakoff et al., 2003; Podsakoff et al., 2012).

A supplementary Gaussian copula diagnostic was conducted to examine whether potential endogeneity concerns altered the substantive interpretation of the structural model. This analysis was treated as a sensitivity check rather than as the primary basis for inference, following guidance on copula-based diagnostics in PLS-SEM research (Park & Gupta, 2012; Hult et al., 2018).

4. Results

4.1 Measurement Model

Table 4 summarizes the reflective measurement model results. Standardized item loadings ranged from 0.676 to 0.821. Items PC01 and KS01 had relatively lower loadings but were retained because the construct-level reliability and validity statistics remained acceptable, and the items captured important aspects of the constructs. Cronbach's alpha (0.713–0.803), rho_a (0.720–0.806), composite reliability (0.822–0.871), and AVE (0.536–0.628) were within acceptable ranges. These findings support acceptable internal consistency, construct reliability, and convergent validity.

Table 4. Reflective measurement model

Construct	Item	Loading	Cronbach's alpha	rho_a	CR	AVE
Human capital	HC01	0.796	0.797	0.802	0.867	0.621
	HC02	0.813				
	HC03	0.812				
	HC04	0.728				
Psychological capital	PC01	0.688	0.713	0.720	0.822	0.536
	PC02	0.773				
	PC03	0.732				
	PC04	0.734				
Innovation capability	IC01	0.791	0.803	0.806	0.871	0.628
	IC02	0.821				
	IC03	0.779				
	IC04	0.779				
Technology adoption	TA01	0.714	0.735	0.739	0.834	0.558
	TA02	0.720				
	TA03	0.810				
	TA04	0.740				
Knowledge sharing	KS01	0.676	0.724	0.732	0.827	0.545
	KS02	0.770				
	KS03	0.740				
	KS04	0.765				

Note(s): CR = composite reliability; AVE = average variance extracted. Item codes refer to valid questionnaire items retained for the measurement model.

Discriminant validity was evaluated based on the heterotrait-monotrait (HTMT) ratio. As illustrated in Table 5, all HTMT values fell below the conservative threshold of 0.85. The maximum HTMT value was 0.653, observed between psychological capital and knowledge sharing, suggesting a moderate correlation between the two constructs while indicating no clear discriminant validity concern.

Table 5. Discriminant Validity Results (HTMT Criterion)

Construct	HC	IC	KS	PC	TA
HC	—				
IC	0.427	—			
KS	0.435	0.498	—		
PC	0.409	0.484	0.653	—	
TA	0.398	0.388	0.382	0.351	—

4.2 Common Method Bias and Collinearity

Table 6 summarizes the diagnostic results for common method bias and collinearity. Harman's single-factor test showed that the first unrotated factor explained 27.26% of the total variance, which is considerably lower than the standard 50% cutoff, suggesting that a single dominant method factor was unlikely to account for the results. The inner VIF values for the core structural model ranged from 1.032 to 1.429, indicating that severe collinearity was unlikely to be a concern.

Table 6. Common method bias and structural collinearity diagnostics

Diagnostic check	Result	Interpretation
First unrotated factor	27.26%	Below the conventional 50% threshold
Main-model inner VIF range	1.032−1.429	No severe inner-model collinearity

Note(s): The first unrotated factor was calculated using the retained reflective indicators. The VIF range refers to the main theoretically specified PLS-SEM model.

4.3 Structural Model and Hypothesis Tests

The model accounted for 20.2% of the variance in innovation capability and 17.9% of the variance in technology adoption, suggesting modest explanatory power. This level of explanatory power should be interpreted in light of the model's focus on internal readiness, innovation capability, and knowledge sharing rather than the full set of institutional, economic, infrastructural, and policy-related determinants of adoption. Effect sizes were generally small to small-to-moderate, as reported in Table 7.

Bootstrapping with 5,000 resamples was used to test the structural paths. As shown in Table 8, human capital was positively associated with innovation capability ($\beta = 0.259$, $t = 5.021$, $p = 0.001$) and technology adoption ($\beta = 0.191$, $t = 3.742$, $p = 0.001$), supporting H1 and H2. Psychological capital was positively associated with innovation capability ($\beta = 0.293$, $t =$

6.304, p = 0.001), supporting H3. Its direct association with technology adoption was not significant (β = 0.100, t = 1.602, p = 0.109), so H4 was not supported. Innovation capability was positively associated with technology adoption (β = 0.131, t = 2.504, p = 0.012), supporting H5.

The indirect effects reported in Table 9 show that innovation capability mediated the relationships between human capital and technology adoption (β = 0.034, t = 2.188, p = 0.029) and between psychological capital and technology adoption (β = 0.038, t = 2.357, p = 0.018). H6 and H7 were therefore supported.

Table 7. Structural explanatory power and effect sizes

Structural Metric	Indicator	Value	Interpretation
R^2 Coefficient	IC	0.202	Modest explanatory power
	Adjusted R^2 for IC	0.198	Stable after adjustment
	TA	0.179	Modest explanatory power
	Adjusted R^2 for TA	0.169	Stable after adjustment
Effect size	HC → IC	0.076	Small-to-moderate contribution
	PC → IC	0.097	Small-to-moderate contribution
	HC → TA	0.036	Small contribution
	PC → TA	0.009	Very small direct contribution
	IC → TA	0.016	Small contribution
	KS → TA	0.013	Small lower-order contribution
	KS × IC → TA	0.026	Small interaction effect

Note(s): IC = innovation capability; TA = technology adoption; HC = human capital; PC = psychological capital; KS = knowledge sharing. The path from knowledge sharing to technology adoption is included as a lower-order main effect for estimating the moderation model. It is reported for model completeness rather than evaluated as an independent hypothesis.

Table 8. Direct effects and hypothesis-testing results

Hypothesis	Path	β	STDEV	t	p	Decision
H1	HC → IC	0.259	0.052	5.021	0.001	Supported
H2	HC → TA	0.191	0.051	3.742	0.001	Supported
H3	PC → IC	0.293	0.047	6.304	0.001	Supported
H4	PC → TA	0.100	0.062	1.602	0.109	Not supported
H5	IC → TA	0.131	0.052	2.504	0.012	Supported
Lower-order path	KS → TA	0.123	0.054	2.263	0.024	Retained for moderation estimation
H8	KS × IC → TA	−0.137	0.046	2.978	0.003	Supported

Note(s): β = standardized path coefficient; STDEV = bootstrapped standard deviation. The path from knowledge sharing to technology adoption is included as a lower-order main effect for estimating the moderation model. It is reported for model completeness rather than evaluated as an independent hypothesis.

Table 9. Indirect and total effects

Effect type	Relationship	β	STDEV	t	p	Interpretation
Indirect effect	HC → IC → TA	0.034	0.016	2.188	0.029	Significant mediation
Indirect effect	PC → IC → TA	0.038	0.016	2.357	0.018	Significant mediation
Total effect	HC → TA	0.225	0.050	4.505	0.001	Significant overall effect
Total effect	PC → TA	0.138	0.058	2.379	0.017	Significant overall effect

Note(s): Total effects include both direct and indirect components. The non-significant direct relationship between PC and TA should be interpreted together with the significant indirect and total relationships.

4.4 Moderation, Prediction, and Sensitivity Checks

Knowledge sharing had a positive lower-order association with technology adoption ($\beta = 0.123$, $t = 2.263$, $p = 0.024$). In addition, the interaction between knowledge sharing and innovation capability was negative and significant ($\beta = -0.137$, $t = 2.978$, $p = 0.003$), supporting H8. The simple slope results presented in Table 10 further indicate that knowledge sharing attenuates the positive relationship between innovation capability and technology adoption. Specifically, the linkage is strongest at low levels of knowledge sharing ($\beta = 0.268$), relatively weaker at the mean ($\beta = 0.131$), and close to zero at high levels of knowledge sharing ($\beta = -0.006$). Figure 2 illustrates this conditional pattern. This pattern indicates that, on average, knowledge sharing is positively related to adoption. However, intensive sharing may weaken the immediate relationship between innovation capability and adoption because farmers have more information to compare and verify before acting.

Table 10. Conditional effects under different levels of knowledge sharing

Level of knowledge sharing	IC → TA	HC → IC → TA	PC → IC → TA
Low KS (−1 SD)	0.268	0.070	0.079
Mean KS	0.131	0.034	0.038
High KS (+1 SD)	−0.006	−0.002	−0.002

Note(s): IC = innovation capability; TA = technology adoption; HC = human capital; PC = psychological capital; KS = knowledge sharing. Conditional effects are reported to interpret the significant KS × IC interaction.

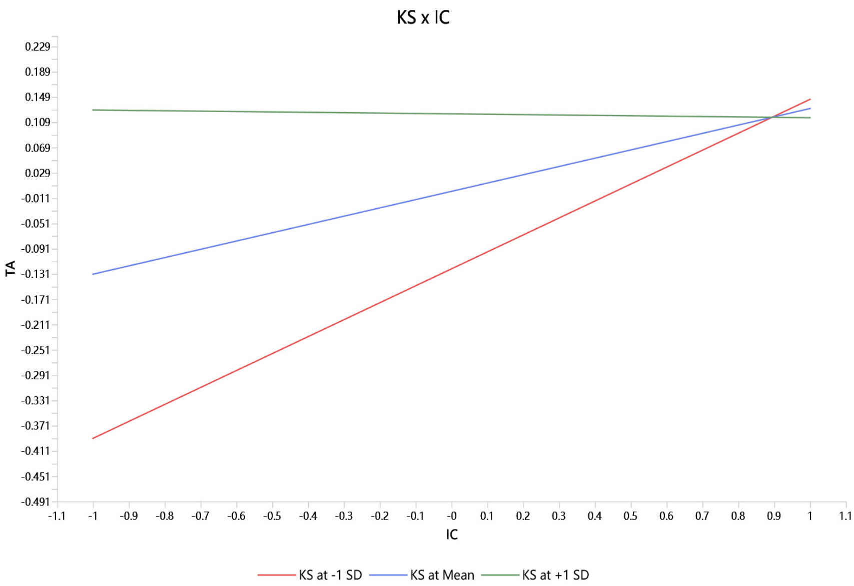

Figure 2. Moderating effect of knowledge sharing

Note(s): The slopes represent the conditional relationship between innovation capability and technology adoption at low, mean, and high levels of knowledge sharing. The interaction term was negative and significant, indicating that the relationship weakened as knowledge sharing increased.

PLSpredict produced positive Q^2_predict values for innovation capability and technology adoption, indicating predictive relevance (Table 11). CVPAT further showed that the PLS-SEM model outperformed the indicator-average benchmark and had a modest overall advantage over the linear model benchmark (Table 12).

The supplementary Gaussian copula specification was used solely as a sensitivity diagnostic, as copula-expanded models may introduce high collinearity among constructed terms. The copula terms did not provide stable evidence that potential endogeneity altered substantive interpretation. Therefore, the main interpretation is based on the theoretically specified PLS-SEM model, and the findings are reported as associations rather than causal estimates.

Table 11. Construct-level out-of-sample PLSpredict diagnostics

Endogenous construct	Q^2_predict	RMSE	MAE	Interpretation
Innovation capability	0.187	0.908	0.700	Positive predictive relevance
Technology adoption	0.134	0.935	0.719	Positive predictive relevance

Note(s): Q^2_predict values above zero indicate predictive relevance. RMSE = root mean squared error; MAE = mean absolute error.

Table 12a. CVPAT comparison with the indicator-average benchmark

Comparison	PLS	IA	Difference	t	p	Interpretation
IC: PLS-SEM vs IA	0.467	0.528	−0.061	4.092	0.001	PLS-SEM outperforms IA
TA: PLS-SEM vs IA	0.581	0.628	−0.047	3.993	0.001	PLS-SEM outperforms IA
Overall: PLS-SEM vs IA	0.524	0.578	−0.054	5.387	0.001	PLS-SEM outperforms IA overall

Table 12b. CVPAT comparison with the linear model benchmark

Comparison	PLS	LM	Difference	t	p	Interpretation
IC: PLS-SEM vs LM	0.467	0.464	0.003	0.363	0.717	No advantage over LM
TA: PLS-SEM vs LM	0.581	0.609	−0.027	4.073	0.001	PLS-SEM outperforms LM
Overall: PLS-SEM vs LM	0.524	0.536	−0.012	2.433	0.015	Modest overall advantage

Note(s): IA = indicator-average benchmark; LM = linear model benchmark; IC = innovation capability; TA = technology adoption. Negative differences indicate lower prediction loss for the PLS-SEM model than for the benchmark model.

5. Discussion

5.1 Theoretical Implications

The findings refine the internal-readiness explanation of smallholder technology adoption in three ways. First, the results suggest a multifaceted role for human capital in adoption decisions. Human capital was associated with technology adoption both directly and indirectly through innovation capability. This pattern suggests that farmers' knowledge of farming, production experience, and on-site problem-solving skills do not merely enhance their basic understanding of new agricultural practices. Instead, these resources support key steps in the practical decision-making process, including evaluating, testing, and adapting innovative techniques before formal adoption. Such findings align with prior adoption literature, which regards farmer education and capacity building as important but context-dependent correlates of agricultural technology utilization (Ruzzante et al., 2021; Arslan et al., 2022).

Second, this study clarifies the unique role of psychological capital. Unlike human capital, psychological capital appears to be linked to adoption mainly through the mediating pathway of innovation capability. Farmers with higher levels of confidence, optimism, hope, and resilience were more likely to report stronger information searching, field experimentation, and localized adjustment. Nevertheless, after controlling for human capital and innovation capability, the direct association between psychological capital and adoption becomes statistically insignificant. This outcome suggests that positive psychological traits alone may be insufficient for actual adoption behavior. Their role appears to be stronger when these psychological resources are translated into learning, experimentation, and practical problem-solving (Luthans et al., 2007; Avey et al., 2011; Chindasombatcharoen et al., 2024).

Third, this study identifies knowledge sharing as a boundary condition in the innovation capability–adoption relationship. The positive lower-order association suggests that active knowledge exchange is associated with farmers' technology uptake. However, the negative interaction suggests that the innovation capability–adoption relationship becomes weaker as knowledge sharing increases. This result should not be interpreted as evidence that knowledge sharing hinders technology adoption. A plausible explanation is that information-rich environments alter how farmers deploy their innovation capability. When information sources are abundant, farmers with higher innovation capability may invest more effort in comparing information, assessing credibility, and verifying whether a practice is suitable for their own production conditions. In information-scarce environments, innovation capability may be more directly related to adoption. In contrast, in information-rich environments, the same capability may be partially used for screening, interpretation, and adjustment before adoption. This explanation aligns with research on knowledge transfer and agricultural knowledge networks, which shows that knowledge exchange can support learning but also requires screening, interpretation, and contextualization before use (Argote & Ingram, 2000; Szulanski, 1996; Izadi et al., 2024; Park, 2025; Tumwebaze et al., 2025).

5.2 Practical Implications

The empirical results offer practical implications for agricultural extension agencies, farmer cooperatives, and grassroots agricultural service providers. Extension work should move beyond one-way delivery of technical information. For small-scale farming households, limited access to information is not the only obstacle to adoption. Instead, many farmers may struggle to judge whether improved farming practices fit their unique production conditions. Extension services should prioritize helping farmers conduct targeted assessments of their land features, labor supply, access to machinery, input capacity, and potential production risks. Training programs may be more useful when they incorporate field diagnosis, comparison of alternative practices, small-scale trials, and locally tailored adaptation guidance.

Second, the findings underline the value of improving farmers' psychological readiness. Enhancing farmers' confidence and risk resilience may support technology adoption, but psychological readiness alone is unlikely to be sufficient without practical learning opportunities. Farmers need field-based opportunities to observe, test, and solve operational problems related to new farming techniques. Demonstration plots, peer learning activities, and follow-up technical support may help farmers turn psychological readiness into sustained learning routines and more stable experimentation practices. In this sense, confidence and persistence are better viewed not simply as personal traits, but as resources that can support on-farm experimentation and practical problem-solving.

Third, this study provides new insights for optimizing rural knowledge-sharing practices. Increasing exposure to information alone may not be sufficient to support adoption. It is equally important to improve the quality, consistency, and local relevance of shared agricultural information. Cooperatives, model farmers, grassroots extension stations, and digital agricultural service platforms can assist farmers in screening credible technical guidance and avoiding confusion from fragmented, conflicting information, especially when farmers obtain information from multiple channels simultaneously. Standardized technical explanations, authoritative information sources, and localized practical cases can reduce farmers' burden of verifying information and support the practical application of new agricultural techniques in daily production.

5.3 Limitations and Future Research

This study is subject to several limitations. First, the empirical analysis draws on cross-sectional, self-reported survey data. As such, the documented relationships reflect correlational patterns rather than definitive causal effects, and this design cannot capture how farmers' internal readiness, innovation capability, and technology adoption change over time. Future research can adopt longitudinal or quasi-experimental designs to examine better temporal relationships and the possible causal processes underlying adoption behavior.

Second, the empirical context is confined to crop smallholders in Henan Province. Although Henan is an important agricultural province with widespread smallholder crop farming, the single-province setting may limit the external validity of the findings. Cross-regional and cross-crop comparative studies are therefore needed to distinguish context-specific patterns from generalizable mechanisms.

Third, this study focuses primarily on farmers' internal resources, innovation capability, and knowledge sharing to clarify the internal readiness mechanism. While this focus keeps the model theoretically focused, it excludes a range of external contextual factors that may influence adoption. Government support, infrastructure endowment, market access, extension service quality, digital literacy, subsidy policies, and agricultural service systems all potentially shape farmers' technology uptake. Integrating these contextual factors in future models can help identify boundary conditions and improve the model's overall explanatory capacity.

6. Conclusion

This study investigates the association between farmers' internal readiness and agricultural technology adoption within smallholder crop production contexts. The results show that human capital is associated with technology adoption both directly and indirectly through innovation capability. By contrast, psychological capital is linked to adoption mainly through its relationship with innovation capability, with a limited direct relationship with adoption. Furthermore, knowledge sharing shows a dual pattern: active knowledge exchange is positively related to technology uptake, whereas intensive knowledge exchange weakens the positive relationship between innovation capability and immediate adoption.

Collectively, these findings suggest that smallholder technology adoption cannot be attributed only to external information access; it also depends on farmers' information processing, practical value assessment, localized field testing, and adaptive adjustment to production conditions. For agricultural extension and policy design, the results imply that technology promotion should move beyond simple information dissemination. More attention should be given to strengthening farmers' technical diagnosis, adaptive learning, and contextual judgment of externally acquired agricultural knowledge.

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Author contributions

Ke Li was responsible for conceptualization, methodology, investigation, data curation, formal analysis, and drafting the manuscript. Kartinah Ayupp provided supervision, conceptual and methodological guidance, and critical revision of the manuscript. Both authors read and approved the final manuscript.

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Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Informed consent

Obtained.

Ethics approval

The Publication Ethics Committee of the Macrothink Institute.

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The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data sharing statement

No additional data are available.

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Appendix A. Measurement Items and Sources

The questionnaire was administered in Chinese. The English items reported below are translations prepared for manuscript reporting purposes. All constructs were measured using a five-point Likert-type scale ranging from 1 = strongly disagree to 5 = strongly agree. Respondents were asked to indicate the extent to which each statement described their household's farming situation, technology-use behavior, or their own role as the main household farming decision-maker.

Human capital, innovation capability, and technology adoption were phrased at the household level because technology-related decisions and implementation activities were treated as household-level farming decisions. Psychological capital and knowledge sharing were phrased at the respondent level because these constructs capture the psychological resources and knowledge-exchange behavior of the main farming decision-maker.

Table A1. Measurement items and sources

Construct	Code	Measurement item	Main meaning	Sources and contextual adaptation
Human capital	HC01	Our household has sufficient farming knowledge to understand improved agricultural practices.	Farming knowledge	Adapted from farmer-capacity and agricultural technology-adoption research; contextualized to farming knowledge, practical skills, experience-based judgment, and problem-solving competence (Ruzzante et al., 2021; Arslan et al., 2022; Manzoor et al., 2025).
Human capital	HC02	Our household has the practical skills needed to apply improved farming methods.	Practical farming skills	
Human capital	HC03	Our household can use farming experience to judge whether a new practice is suitable for our production conditions.	Experience-based judgment	
Human capital	HC04	Our household can solve practical problems that arise when using improved farming methods.	Problem-solving competence	
Psychological capital	PC01	I am confident that our household can handle difficulties in agricultural production.	Self-efficacy	Adapted from psychological-capital research; contextualized to confidence, hope, optimism, and resilience in farming uncertainty (Luthans et al., 2007; Avey et al., 2011; Chindasombatcharoen et al., 2024).
Psychological capital	PC02	When facing farming difficulties, I can usually find ways to move forward.	Hope	

Psychological capital	PC03	I generally expect that our farming situation can improve through effort and adjustment.	Optimism	
Psychological capital	PC04	Even when farming results are not ideal, I can recover and continue trying.	Resilience	
Innovation capability	IC01	Our household actively seeks useful information on improved farming practices.	Knowledge search	
Innovation capability	IC02	Our household compares different farming methods before deciding which to use.	Evaluation of alternatives	Adapted from dynamic capability, absorptive capacity, and smallholder innovation-capability research; contextualized to information search, evaluation, experimentation, and adaptation (Cohen & Levinthal, 1990; Teece et al., 1997; Teece, 2007; Jalotjot & Tokuda, 2024).
Innovation capability	IC03	Our household is willing to try new farming practices on a small scale before wider use.	Experimentation	
Innovation capability	IC04	Our household can adjust improved farming practices according to local land, labor, and production conditions.	Adaptation and reconfiguration	
Technology adoption	TA01	Our household has used improved farming techniques or practices in actual production.	Actual technology use	
Technology adoption	TA02	Our household continues to use improved farming practices after initial trial or exposure.	Continued use	Adapted from agricultural technology-adoption and digital agriculture research; contextualized to actual use, continued use, routinization, and expansion intention (Ruzzante et al., 2021; Mao et al., 2024; Tao et al., 2024; Zhang et al., 2024).
Technology adoption	TA03	Improved farming technologies or practices have become part of our regular production activities.	Routine implementation	
Technology adoption	TA04	Our household is willing to expand the use of effective, improved farming practices when conditions allow.	Adoption expansion intention	

Knowledge sharing	KS01	I often exchange farming information or experiences with other farmers.	Peer information exchange	Adapted from knowledge-transfer, social-learning, and agricultural knowledge-management research; contextualized to peer exchange, willingness to share, advice seeking, and learning from shared knowledge (Argote & Ingram, 2000; Szulanski, 1996; Izadi et al., 2024; Manda et al., 2024; Park, 2025; Tumwebaze et al., 2025).
Knowledge sharing	KS02	I am willing to share useful farming knowledge or experience with others.	Willingness to share	
Knowledge sharing	KS03	I can obtain practical advice from other farmers or related actors when facing production problems.	Knowledge receiving	
Knowledge sharing	KS04	Exchanging knowledge with others helps me understand different ways to improve farm production.	Learning from shared knowledge	

Note(s): HC = human capital; PC = psychological capital; IC = innovation capability; TA = technology adoption; KS = knowledge sharing.

Appendix B. Construct-Level Descriptive Statistics and Correlations

Table B1. Construct-Level Descriptive Statistics and Correlations

Construct	Mean	SD	HC	PC	IC	TA	KS
HC	2.985	0.727	—				
PC	3.379	0.507	0.303	—			
IC	3.585	0.575	0.342	0.367	—		
TA	3.148	0.589	0.304	0.256	0.297	—	
KS	3.561	0.534	0.319	0.472	0.383	0.279	—

Note(s): HC = human capital; PC = psychological capital; IC = innovation capability; TA = technology adoption; KS = knowledge sharing. Composite scores were calculated using the retained indicators after sequential renumbering: HC01–HC04, PC01–PC04, IC01–IC04, TA01–TA04, and KS01–KS04. Correlations are reported for descriptive transparency and are not used as substitutes for the reflective measurement model and HTMT assessments.

Appendix C. Gaussian copula sensitivity diagnostic

Table C1. Gaussian copula sensitivity diagnostic

Diagnostic item	Result	Interpretation
Main-model inner VIF	1.032–1.429	No serious collinearity in the theoretically specified model
Copula terms	Mostly non-significant	No stable copula-based evidence alters the main conclusions
Copula-expanded VIF	Several values above 10; some above 40–50	High collinearity in the expanded diagnostic specification; results interpreted cautiously
Analytical decision	Model retained	Copula results are treated as a supplementary sensitivity diagnostic

Note(s): The Gaussian copula-expanded specification was used only to examine potential endogeneity concerns. Because the expanded diagnostic specification showed high collinearity among constructed terms, the main interpretation is based on the theoretically specified PLS-SEM model.