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From Financial and Human Capital to Technology Adoption Readiness: Resource Conversion Among Smallholder Farmers in Henan, China

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Abstract

In smallholder agriculture, access to finance, training and external services does not, by itself, explain how farm households convert available support into workable production decisions. This study examines how financial and human capital are linked to innovation capability, technology adoption readiness and farmer-reported performance in smallholder farming in Henan Province, China. Grounded in the resource-based view and a context-sensitive reading of dynamic capability, the study treats capital resources as enabling conditions whose value depends on their conversion into adaptive judgement and technology-specific readiness. Cross-sectional survey data from 565 farm households were analysed using partial least squares structural equation modelling. Financial and human capital were positively associated with innovation capability and technology adoption readiness, but their direct associations with farmer-reported performance were not statistically supported. Innovation capability was linked to technology adoption readiness, whereas its direct association with farmer-reported performance was not supported. Technology adoption readiness showed the strongest association with farmer-reported performance and formed the main statistically supported indirect pathway linking capital resources to performance. The findings suggest that, under smallholder farming constraints, resource conversion depends less on resource access alone than on household-level adjustment, service conditions and readiness to use feasible technologies.

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AQ1

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Keywords

Smallholder farmers, resource conversion, technology adoption readiness, innovation capability, resource-based view, China

Introduction

Many smallholder farmers are increasingly exposed to credit, training, extension advice, machinery services and other forms of external support. The difficulty is that such access still has to pass through household judgement. A farmer considering a new practice must ask whether it is affordable, understandable, manageable and compatible with land conditions, labour availability, seasonal workload and risk tolerance. For this reason, technology-related change in smallholder agriculture is better treated as judgement, learning, trial and adjustment rather than as a simple decision to adopt or reject a technology (Glover et al. 2019). Recent adoption studies also suggest that farmers do not assess a new practice in isolation. Their judgement is shaped by uncertainty, learning conditions, farm characteristics and the specific attributes of the technology being considered (Chavas and Nauges 2020; Schulz and Börner 2023).

The Chinese case is useful for this question because agricultural modernisation has moved forward while household-based smallholder farming has remained in place. For many farmers, modern agriculture is not encountered through a fully internalised farm organisation. Rather, it is accessed through a set of service interfaces: extension agents provide advice, machinery operators carry out field operations, cooperatives help organise access and local service markets make certain technologies usable. These arrangements expand farmers' options, but they do not remove the conditions within which household decisions are made. Fragmented plots, family labour arrangements, seasonal pressure and unequal capacity to take up external support remain important. Studies on rural China have made this point in different ways. Cooperatives, agricultural innovation systems and machinery-service markets can connect smallholders with modern agriculture, but whether farmers actually benefit from these channels depends on service quality, local coordination and household-level judgement (Chen et al. 2024; Zhong et al. 2023; Zou and Mishra 2024). Labour ageing further complicates this conversion, especially when a new practice requires learning, coordination or additional risk-bearing (Ren et al. 2023; Yu et al. 2023). Henan therefore offers a relevant empirical setting as a grain-producing province where household crop farming, outsourced mechanisation, extension support and fragmented farmland coexist.

Previous studies have explained many factors that shape technology adoption. Farmers' decisions are known to vary with learning opportunities, uncertainty, household conditions and the characteristics of the technology itself (Chavas and Nauges 2020; Schulz and Börner 2023). In the Chinese context, a related stream of research has shown that cooperatives, agricultural innovation systems and machinery-service markets help smallholders connect with modern agriculture (Chen et al. 2024; Zhong et al. 2023; Zou and Mishra 2024). These studies are valuable, but one part of the process remains insufficiently examined. Once

resources are available, how do farm households judge them, try them out, compare their usefulness and gradually become ready to use a technology? This question matters because smallholder farmers do not usually convert resources through formal organisational routines or clearly codified innovation procedures. In practice, conversion is more likely to occur in modest, situated ways: through household experimentation, comparisons among service options, seasonal adjustment and step-by-step refinement of cultivation practices.

To build this argument, the study places the resource-based view in dialogue with a context-sensitive understanding of dynamic capability. The resource-based view is useful because it draws attention to financial and human capital. However, its original firm-centred assumptions need careful treatment in household farming; they should not be transferred directly to smallholders as though farm households were formal business organisations (Barney 1991; Furr and Eisenhardt 2021). In this context, resources are often incomplete, partly provided through external services or public support, and not always easy to apply consistently across production seasons. Their value depends on whether farmers can interpret, combine and use them in workable production decisions. The dynamic capability perspective helps specify this conversion process, although its usual emphasis on formal routines, specialised knowledge systems and organisational reconfiguration also requires reinterpretation in this context (Teece 2007). Here, innovation capability refers to a practical capacity for experimentation, evaluation and adjustment, while technology adoption readiness refers to a more specific judgement about whether a feasible technology appears useful, manageable and worth using when conditions allow (Cimino et al. 2024; Giua et al. 2022). Using cross-sectional survey data from 565 farm households in Henan, the study examines theory-based associations among financial capital, human capital, innovation capability, technology adoption readiness and farmer-reported performance.

This study extends rural management research in three ways. First, it shifts the resource-based argument from resource possession to resource conversion in smallholder farming. Second, it offers a smallholder reading of dynamic capability by suggesting that adaptive capability is carried less by firm-like internal routines than by the household-service interface, seasonal micro-adjustments and farmers' situated judgement. Third, it separates innovation capability from technology adoption readiness. This distinction helps explain why general adaptive capability may support readiness for feasible technology use without being directly linked to short-term farmer-reported performance.

Literature Review

Financial and Human Capital as Enabling Resources

The resource-based view offers an initial basis for explaining why some farm households are more capable than others of adjusting their production practices. Financial and human capital matter because they shape what farmers can afford, understand, compare and manage. In smallholder farming, however, these resources should not be treated as direct equivalents of firm-owned strategic

assets. Farm households usually make production decisions under multiple constraints simultaneously. Liquidity may be limited, training opportunities may differ across villages and households, land is often small and fragmented, and decisions are tied to family labour and seasonal risk. For this reason, financial and human capital cannot be assumed to have value in and of themselves. Their relevance depends on whether farmers can translate them into workable production judgement and technology-related readiness.

Financial capital matters first because a new practice often has to be paid for before any return is realised. Farmers may need money to buy inputs, hire machinery services or try a different cultivation method, and they are less likely to do so when the attempt would put immediate pressure on household finances. Credit access, household liquidity, external financial support and some ability to absorb risk therefore give farmers room to prepare and experiment. Evidence from Chinese family farms also indicates that rural credit is linked to technology adoption and scale-related efficiency, although the strength and meaning of this link vary by credit type, the technology involved and the production context (Cai et al. 2024; Wang et al. 2025). For this reason, financial capital is more likely to support experimentation and readiness than to produce an immediate improvement in farmer-reported performance.

H_{1a} : Financial capital is associated positively with innovation capability.

H_{1b} : Financial capital is associated positively with technology adoption readiness.

H_{1c} : Financial capital is associated positively with farmer-reported performance.

Human capital is different from financial capital. It does not give farmers money to try a new practice, but it may help them make better sense of the choices before them. Farmers with more education, training, farming experience or management experience are usually better placed to identify production problems, understand technical advice, compare service options and judge whether a practice is workable under their own land, labour and seasonal conditions. Training and demonstration may reduce learning barriers, but the use of that knowledge still depends on service availability, production risk and the household's ability to act on what has been learned (Mgendi et al. 2022; Schulz and Börner 2023). Human capital is hypothesised to be more closely associated with innovation capability and technology adoption readiness than with farmer-reported performance, although a direct association is included as a baseline.

H_{2a} : Human capital is associated positively with innovation capability.

H_{2b} : Human capital is associated positively with technology adoption readiness.

H_{2c} : Human capital is associated positively with farmer-reported performance.

Innovation Capability and Technology Adoption Readiness

Innovation capability is understood here as a practical household-level capacity rather than formal research and development (R&D) capability or completed

technology adoption. In smallholder farming, innovation is more likely to appear in limited-scale experimentation, process adjustments, comparisons of machinery service options and changes in planting decisions made in response to weather, market signals and labour availability. Recent research highlights learning, process improvement, resource integration and adaptive adjustment as core dimensions of innovation-related capacity, while work on smallholder innovation shows that such capability is often collaborative, practical and locally embedded rather than formal and organisationally codified (Jalotjot and Tokuda 2024; Moreira et al. 2024). In this study, innovation capability refers to farmers' capability to experiment, evaluate and adjust farming practices under household-level constraints.

This is why innovation capability is expected to relate to technology adoption readiness. Farmers who can try out ideas, compare alternatives and make adjustments have a stronger basis for judging a technology. Farmers can consider whether a technology is useful, practical and compatible with the farm's existing routines. Readiness and actual adoption, however, should still be distinguished. When costs are high, labour is limited, land is fragmented, services are not readily available or the next season remains uncertain, a farmer may regard a technology as promising and manageable but still delay the decision to use it. Studies on digital and smart farming make a similar distinction between perceived usefulness, complexity, intention and actual adoption behaviour (Cimino et al. 2024; Giua et al. 2022).

H₃: Innovation capability is associated positively with technology adoption readiness.

A direct link between innovation capability and farmer-reported performance is not straightforward. The ability to evaluate and adjust farming practices can help farmers identify workable options and avoid unsuitable ones. However, such ability may take time to affect income, productivity or profitability, and its effect may not be visible within a single production period. Some adjustments may reduce losses rather than increase visible returns; others may require time or complementary services before their value becomes apparent. Technology adoption readiness is treated as the construct more closely linked to farmer-reported performance.

H₄: Innovation capability is associated positively with farmer-reported performance.

H₅: Technology adoption readiness is associated positively with farmer-reported performance.

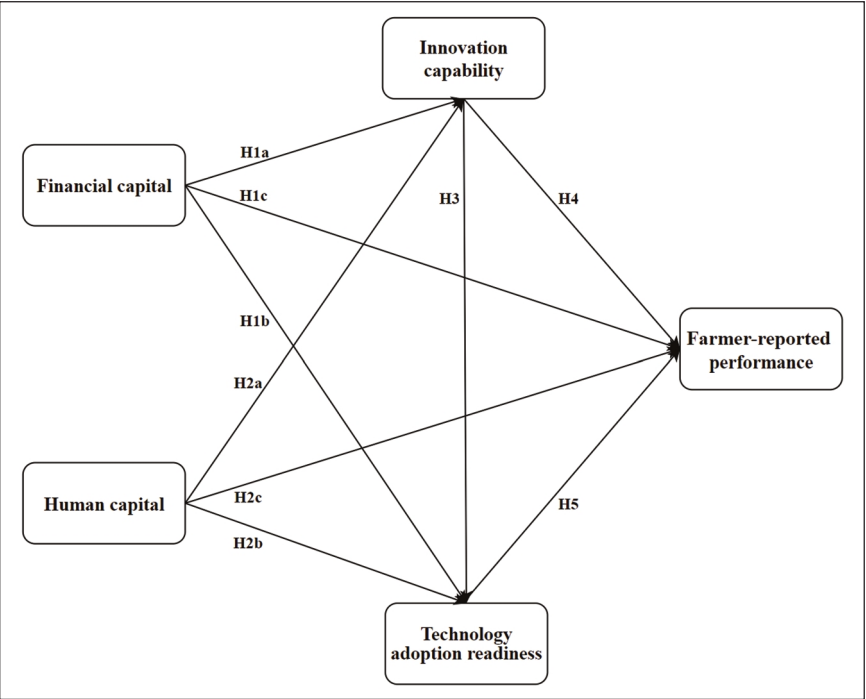
Indirect and Sequential Associations

The preceding arguments suggest that financial and human capital may be linked to farmer-reported performance through intermediate conversion mechanisms. Credit, liquidity, training and experience have to be interpreted and used in relation to production problems, local service options, seasonal timing and household risk tolerance. Innovation capability represents one possible pathway

in this process. Farmers with stronger financial or human capital may be better placed to experiment with practices, evaluate alternatives and adjust routines. This adaptive capacity may then be associated with farmer-reported performance when it helps households avoid unsuitable choices or improve production decisions.

- H_{6a} : Financial capital is indirectly associated with farmer-reported performance through innovation capability.
- H_{7a} : Human capital is indirectly associated with farmer-reported performance through innovation capability.

Technology adoption readiness represents a second and more technology-specific pathway. Financial capital may make a feasible technology appear more affordable and less risky, while human capital may help farmers judge whether it is understandable and manageable. Readiness is therefore understood as a stage before actual adoption. It captures the farmer’s judgement that a feasible technology is worth considering and could be used once farm and service conditions make its use possible.



AQ2 **Figure 1.** Conceptual Framework.

Note: The indirect and sequential indirect hypotheses are assessed through bootstrapped indirect effects.

H_{6b} : Financial capital is indirectly associated with farmer-reported performance through technology adoption readiness.

H_{7b} : Human capital is indirectly associated with farmer-reported performance through technology adoption readiness.

The model therefore places innovation capability before technology adoption readiness. This ordering should not be read as a demonstrated temporal sequence, since the data are cross-sectional. It is a theoretical ordering: a farmer's broader ability to try, compare and adjust practices is expected to provide the basis for judging whether a particular technology is useful, manageable and worth using. Because the data are cross-sectional, the sequential path is interpreted as a theory-based modelling structure rather than as evidence that the process unfolds in this exact order over time.

H_8 : Financial capital is indirectly associated with farmer-reported performance sequentially through innovation capability and technology adoption readiness.

H_9 : Human capital is indirectly associated with farmer-reported performance sequentially through innovation capability and technology adoption readiness.

Methodology

Research Design and Empirical Setting

This study draws on a cross-sectional field survey of smallholder farm households in Henan Province, China. The unit of analysis was the farm household, and the respondent was the household head or the main person responsible for crop-production decisions. As the survey provides cross-sectional evidence, the findings should be interpreted as associative rather than as evidence of temporal ordering or causal relationships.

Henan was selected because it is a major grain-producing province where household-based crop farming remains common, while extension support, machinery services, cooperative participation and agricultural modernisation programmes have become increasingly visible. This setting is well suited to examining resource conversion because many households have access to some form of external support. However, their ability to make use of that support remains shaped by land conditions, family labour, seasonal timing, service availability and risk tolerance.

Fieldwork took place from May to October 2024. With assistance from local agricultural extension offices, the research team identified candidate villages in township-level areas across Henan's 18 prefecture-level administrative units and contacted village-level gatekeepers. Candidate villages were selected to ensure field access across different parts of the province. The role of the extension offices was limited to field access and local coordination; they did not distribute questionnaires, observe respondents' answers or access completed questionnaires.

AQ3

Table 1. Respondent and Household Profile (*n* = 565).

Characteristic	Category/Statistic	<i>n</i> /Mean	%/SD
Gender	Male	335	59.3
	Female	230	40.7
Age (years)	25–44	161	28.5
	45–64	398	70.4
	65 and above	6	1.1
Marital status	Single	4	0.7
	Married	541	95.8
	Divorced or widowed	20	3.6
Cooperative membership	Yes	227	40.2
	No	338	59.8
Education level	Non-literate	13	2.3
	Primary education	201	35.6
	Secondary education	342	60.5
	College diploma or above	9	1.6
Farming experience	10 years or below	67	11.8
	11–20 years	161	28.5
	21–30 years	267	47.3
	More than 30 years	70	12.4
Household size	Mean (SD)	5.26	1.344
Farming experience	Mean (SD), years	23.26	7.874
Cultivated land area in 2023	Mean (SD), mu	8.43	5.087

Note: One mu equals 666.67 m² or approximately 0.0667 ha.

Data were gathered through face-to-face interviews, which were considered appropriate because many respondents had long farming experience but relatively limited formal education. In total, 800 households were contacted during the fieldwork. After questionnaires with missing information or poor response quality were excluded, 565 valid cases were retained for analysis, yielding a usable response rate of 70.6%. Although the final sample covered different parts of Henan, it should be interpreted as a geographically varied field sample rather than a probability sample representative of all smallholder households in the province. Participation was voluntary. Before each interview, respondents were informed of the research’s purpose and gave consent to participate. The survey did not collect names, identity numbers, phone numbers or any other information that could directly identify individual respondents.

Measures

Multiple indicators on a five-point Likert scale were used to measure each construct. The measurement items were adapted from prior studies and adjusted to

suit the crop-production context of smallholder farmers in Henan. Since the responses reflected farmers' own assessments, the constructs should be understood as perceived measures rather than objective indicators. Financial capital refers to the perceived sufficiency of financial resources; human capital refers to the perceived adequacy of knowledge and experience; innovation capability captures household-level capacity for adjustment and experimentation; technology adoption readiness reflects farmers' preparedness to consider and use feasible technologies; and performance refers to farmers' self-reported production-related outcomes.

The questionnaire was first prepared in English, and a Chinese version was then developed for field use in Henan. To assess whether the item meanings had been appropriately carried over, the research team used back-translation between English and Mandarin Chinese (Brislin 1970). The Chinese wording was not finalised solely through translation. It was also discussed with agricultural management academics, frontline extension practitioners and several smallholder farmers to ensure the items could be understood in the local crop production setting. The construct measures were based on prior studies and then adjusted for the present research context. Financial capital followed Khattak and Shah (2020), while human capital followed Vidotto et al. (2017). The innovation capability items were based on Moreira et al. (2024) and Jalotjot and Tokuda (2024). Technology adoption readiness was adapted from Chau and Hu (2002) and from relevant technology-acceptance studies, including Davis (1989), Venkatesh et al. (2003), Giua et al. (2022) and Cimino et al. (2024). Farmer-reported performance was captured through farmers' assessments of crop income growth, yield improvement, profit margin and net profit per unit area, using either local comparison points or the previous production year as the reference. All questionnaire items are reported in Appendix A.

Data Analysis

Partial least squares structural equation modelling (PLS-SEM) was conducted in SmartPLS 4 to analyse the dataset (Ringle et al. 2024). PLS-SEM was appropriate for this study because the proposed model comprises multiple latent constructs and theoretically grounded indirect relationships, and because the analysis focuses on explained variance, predictive assessment and association patterns among constructs (Hair et al. 2019).

The measurement model was assessed before the structural model. Indicator loadings, Cronbach's alpha, ρ_a , composite reliability and average variance extracted (AVE) were used to assess internal consistency and convergent validity. Discriminant validity was assessed through the heterotrait–monotrait (HTMT) ratio as well as the Fornell–Larcker criterion (Fornell and Larcker 1981; Henseler et al. 2015). The structural model was then assessed using inner variance inflation factors (VIFs), bootstrapped path coefficients, confidence intervals, R^2 values, effect sizes, PLSpredict and the cross-validated predictive ability test (CVPAT). Bootstrapping was performed using 10,000 subsamples.

Procedural remedies were used to limit the possible influence of common method bias, and statistical diagnostics were conducted to assess its potential influence. Following Podsakoff et al. (2012), the questionnaire used neutral wording, separated measurement blocks and assured respondents of anonymity. Harman’s single-factor diagnostic and full collinearity VIFs were then examined, with the latter used as an additional PLS-SEM diagnostic (Kock 2015). These checks were treated as diagnostic only; they do not prove that common method bias is absent. PLSpredict and CVPAT were used to complement the explanatory assessment with predictive diagnostics (Lienggaard et al. 2021; Sharma et al. 2023; Shmueli et al. 2019).

Analysis and Results

Common Method Bias and Measurement Model

Common method bias was examined before evaluating the measurement model. Harman’s single-factor diagnostic did not indicate that a single factor accounted for most of the variance. The unrotated principal component analysis of the 20 reflective indicators extracted five components with eigenvalues greater than one, and the first component explained 24.645% of the total variance. Full collinearity VIFs were also examined as an additional diagnostic. The values ranged from 1.193 to 1.410, below the 3.3 reference value used in full collinearity assessment.

The measurement model results are reported in Tables 2–6. Indicator loadings ranged from 0.714 to 0.893. Cronbach’s alpha values ranged from 0.726 to 0.853, composite reliability values from 0.829 to 0.901 and AVE values from 0.548 to 0.696. These results provide evidence of acceptable internal consistency and convergent validity. HTMT values ranged from 0.172 to 0.530, and all bootstrapped confidence intervals were below 1. The HTMT value for the IC-TAR construct pair was 0.403, supporting the empirical distinction between the constructs in the measurement model. The Fornell–Larcker criterion was also satisfied.

Table 2. Harman's Single-factor Test.

Component	Initial Eigenvalue	Variance Explained (%)	Cumulative Variance (%)
1	4.929	24.645	24.645
2	2.783	13.915	38.561
3	1.793	8.967	47.528
4	1.453	7.265	54.793
5	1.435	7.176	61.969

Source: Authors' calculations using SPSS.

Notes: The analysis included the 20 reflective indicators. Extraction method: principal component analysis. Rotation method: none.

Table 3. Full Collinearity Variance Inflation Factor (VIF).

Construct	Full Collinearity VIF
FC	1.320
HC	1.361
IC	1.206
TAR	1.410
OP	1.193

Source: Authors' calculations using SmartPLS 4.

Note: FC: Financial capital; HC: Human capital; IC: Innovation capability; OP: Farmer-reported performance; TAR: Technology adoption readiness.

Table 4. Measurement Model Assessment.

Construct	Item	Loading	α	rho_a	CR	AVE
Financial capital	FC1	0.730	0.853	0.864	0.901	0.696
	FC2	0.874				
	FC3	0.893				
	FC4	0.831				
Human capital	HC1	0.808	0.801	0.816	0.869	0.625
	HC2	0.819				
	HC3	0.809				
	HC4	0.721				
Innovation capability	IC1	0.814	0.813	0.822	0.876	0.640
	IC2	0.826				
	IC3	0.758				
	IC4	0.800				
Technology adoption readiness	TAR1	0.714	0.746	0.751	0.840	0.568
	TAR2	0.737				
	TAR3	0.813				
	TAR4	0.748				
Farmer-reported performance	OP1	0.744	0.726	0.730	0.829	0.548
	OP2	0.727				
	OP3	0.733				
	OP4	0.756				

Source: Authors' calculations using SmartPLS 4.

Note: α : Cronbach's alpha; AVE: Average variance extracted; CR: Composite reliability; rho_a: Dijkstra–Henseler reliability.

Structural Model, Direct Paths and Indirect Paths

Structural collinearity was assessed before interpreting the hypothesised paths. Collinearity was not a major concern in the structural model. The inner VIFs

Table 5. Heterotrait–Monotrait (HTMT) Ratios.

Construct Pair	HTMT	2.5%	97.5%
HC–FC	0.525	0.439	0.604
IC–FC	0.264	0.179	0.354
IC–HC	0.402	0.306	0.493
TAR–FC	0.423	0.305	0.540
TAR–HC	0.379	0.270	0.489
TAR–IC	0.403	0.308	0.497
TAR–OP	0.530	0.429	0.626
OP–FC	0.244	0.180	0.331
OP–HC	0.215	0.165	0.324
OP–IC	0.172	0.116	0.283

Source: Authors' calculations using SmartPLS 4.

Notes: FC: Financial capital; HC: Human capital; IC: Innovation capability; OP: Farmer-reported performance; TAR: Technology adoption readiness. All HTMT values are below the conservative 0.85 reference value, and the bootstrapped confidence intervals do not include 1.

Table 6. Fornell–Larcker Criterion.

Construct	FC	HC	IC	TAR	OP
FC	0.834				
HC	0.436	0.790			
IC	0.229	0.343	0.800		
TAR	0.340	0.296	0.319	0.754	
OP	0.167	0.074	0.136	0.395	0.740

Source: Authors' calculations using SmartPLS 4.

Note: FC: Financial capital; HC: Human capital; IC: Innovation capability; OP: Farmer-reported performance; TAR: Technology adoption readiness.

ranged from 1.143 to 1.354, and the largest value occurred on the human capital–farmer-reported performance path. Since all values remained well below the commonly used 3.3 threshold, the model showed no evidence of problematic collinearity. The standardised root mean square residual (SRMR) assessment produced an identical value of 0.081 for the saturated and estimated specifications. Because this value is close to, but slightly above, the 0.08 reference value often used in PLS-SEM reporting, SRMR was treated as supplementary diagnostic information rather than as evidence of strong model fit.

Table 7 reports the explanatory and predictive assessment. The model explained 12.5% of the variance in innovation capability, 18.7% in technology adoption readiness and 16.1% in farmer-reported performance. PLSpredict produced positive Q^2_{predict} values for all three endogenous constructs. Predictive relevance was clearer for technology adoption readiness and innovation capability, with Q^2_{predict} values of 0.130 and 0.116, respectively. The Q^2_{predict} value for

Table 7. Explanatory and Predictive Assessment.

Construct	R^2	Adjusted R^2	Q^2_{predict}	RMSE	MAE
IC	0.125	0.122	0.116	0.944	0.740
TAR	0.187	0.183	0.130	0.936	0.710
OP	0.161	0.155	0.018	0.994	0.763

Source: Authors' calculations using SmartPLS 4.

Note: IC: Innovation capability; MAE = mean absolute error; OP: Farmer-reported performance; Q^2_{predict} : PLSpredict statistic; R^2 : Coefficient of determination; RMSE: root mean square error; TAR: Technology adoption readiness.

Table 8. Cross-validated Predictive Ability Test (CVPAT) Results for Predictive Benchmark Comparisons.

Target Construct	PLS Loss	IA Loss	Difference	<i>t</i> -Value	<i>p</i> Value
IC	0.524	0.565	−0.041	3.790	<.001
TAR	0.603	0.653	−0.050	3.835	<.001
OP	0.515	0.520	−0.005	1.207	.228
Overall	0.547	0.579	−0.032	4.754	<.001
Target Construct	PLS Loss	LM Loss	Difference	<i>t</i> -Value	<i>p</i> Value
IC	0.524	0.514	0.010	1.557	.120
TAR	0.603	0.609	−0.005	1.090	.276
OP	0.515	0.496	0.019	2.270	.024
Overall	0.547	0.540	0.008	1.745	.082

Source: Authors' calculations using SmartPLS 4.

Notes: IA: Indicator-average benchmark; IC: Innovation capability; LM: Linear-model benchmark; OP: Farmer-reported performance; TAR: Technology adoption readiness. Negative differences indicate lower prediction loss for the partial least squares structural equation modelling (PLS-SEM) model than for the benchmark; positive differences indicate higher prediction loss.

farmer-reported performance was much smaller at 0.018. These results suggest that the model is more informative for understanding the two intermediate constructs than for predicting farmer-reported performance.

CVPAT was used as an additional predictive benchmark check. As shown in Table 8, the PLS-SEM model yielded lower prediction loss than the indicator-average benchmark for innovation capability, technology adoption readiness and the overall model comparison. For farmer-reported performance, the PLS-SEM model produced a slightly lower prediction loss than the indicator-average benchmark, but this difference was not statistically significant. When benchmarked against the linear model, the PLS-SEM model did not demonstrate a statistically significant overall predictive advantage at the 5% level; moreover, the linear-model benchmark predicted farmer-reported performance more accurately. These findings point to a restrained reading of the model. It is informative for tracing theory-based associations among resources, capability and readiness, but its ability to predict farmer-reported performance remains limited.

Table 9 shows a consistent pattern. Financial and human capital appeared to work mainly through the intermediate constructs. Both were associated with innovation capability and technology adoption readiness, whereas their direct links with farmer-reported performance were not statistically supported. Thus, H_{1a} , H_{1b} , H_{2a} and H_{2b} were supported, whereas H_{1c} and H_{2c} were not. The results show a distinction between capability and readiness. Innovation capability was associated with technology adoption readiness, as predicted by H_3 , but did not directly translate into farmer-reported performance. Technology adoption readiness, however, was positioned closest to performance in the model and displayed the strongest direct association with it, thereby supporting H_5 .

The mediation analysis provides further clarification of this pattern. When innovation capability was specified as the only mediator, neither financial capital nor human capital showed a statistically significant indirect effect on farmer-reported performance. Accordingly, H_{6a} and H_{7a} were not supported. By contrast, the indirect associations through technology adoption readiness were statistically supported for both financial capital and human capital, supporting H_{6b} and H_{7b} . The sequential indirect associations through innovation capability and technology adoption readiness were also statistically supported, supporting H_8 and H_9 . These sequential associations require careful interpretation since the data are cross-sectional and the coefficient for the financial-capital sequence was small. Table 10 shows that technology adoption readiness had the largest effect size for farmer-reported performance, while the direct paths from financial capital, human capital and innovation capability to farmer-reported performance had trivial effect sizes.

Discussion

Interpretation of Findings

The findings support adoption research that treats technology-related decisions as shaped by learning conditions, uncertainty, technology characteristics and local context, rather than by access alone (Chavas and Nauges 2020; Schulz and Börner 2023). They also qualify a simpler resource-performance reading of the resource-based view. In the sampled households, financial and human capital were not directly linked to farmer-reported performance; their relevance appeared through farmers' capacity to interpret production problems, compare feasible options and prepare for technology use. This matters for rural management because the managerial problem is not only whether smallholders receive resources but also whether those resources can be converted through household judgement and local service conditions. The result also fits recent work on rural China, where cooperatives, agricultural innovation systems and machinery-service markets connect smallholders with modern agriculture but do not remove the need for household-level coordination and judgement (Chen et al. 2024; Zhong et al. 2023; Zou and Mishra 2024).

The financial-capital result clarifies the role of financial resources in this setting. Credit access, liquidity and risk-buffering capacity can make trials less costly and a new practice more feasible. However, these resources may not appear as

Table 9. Direct and Indirect Associations.

Hypothesis	Relationship	β	t-Value	p Value	95% CI	Decision
Direct Associations						
H_{1a}	FC $\rightarrow$ IC	0.098	2.151	.031	[0.011, 0.190]	Supported
H_{1b}	FC $\rightarrow$ TAR	0.239	4.906	<.001	[0.145, 0.335]	Supported
H_{1c}	FC $\rightarrow$ OP	0.063	1.285	.199	[-0.043, 0.148]	Not supported
H_{2a}	HC $\rightarrow$ IC	0.300	6.628	<.001	[0.210, 0.388]	Supported
H_{2b}	HC $\rightarrow$ TAR	0.115	2.507	.012	[0.026, 0.205]	Supported
H_{2c}	HC $\rightarrow$ OP	-0.077	1.305	.192	[-0.195, 0.036]	Not supported
H_3	IC $\rightarrow$ TAR	0.225	5.076	<.001	[0.138, 0.311]	Supported
H_4	IC $\rightarrow$ OP	0.024	0.520	.603	[-0.064, 0.117]	Not supported
H_5	TAR $\rightarrow$ OP	0.388	9.157	<.001	[0.309, 0.476]	Supported
Indirect Associations						
H_{6a}	FC $\rightarrow$ IC $\rightarrow$ OP	0.002	0.466	.641	[-0.007, 0.013]	Not supported
H_{6b}	FC $\rightarrow$ TAR $\rightarrow$ OP	0.093	4.117	<.001	[0.054, 0.143]	Supported
H_{7a}	HC $\rightarrow$ IC $\rightarrow$ OP	0.007	0.505	.613	[-0.020, 0.036]	Not supported
H_{7b}	HC $\rightarrow$ TAR $\rightarrow$ OP	0.045	2.413	.016	[0.011, 0.082]	Supported
H_8	FC $\rightarrow$ IC $\rightarrow$ TAR $\rightarrow$ OP	0.009	2.060	.039	[0.001, 0.017]	Supported
H_9	HC $\rightarrow$ IC $\rightarrow$ TAR $\rightarrow$ OP	0.026	3.214	.001	[0.013, 0.045]	Supported

Source: Authors' calculations using SmartPLS 4.

Note: β : Standardised path coefficient; CI: confidence interval; FC: Financial capital; HC: Human capital; IC: Innovation capability; OP: Farmer-reported performance; TAR: Technology adoption readiness. t-Values are reported as absolute values.

Table 10. f^2 Effect-size Assessment.

Path	f^2
FC to IC	0.009
FC to TAR	0.056
FC to OP	0.004
HC to IC	0.083
HC to TAR	0.012
HC to OP	0.005
IC to TAR	0.054
IC to OP	0.001
TAR to OP	0.146

Source: Authors' calculations using SmartPLS 4.

Note: f^2 : Effect size; FC: Financial capital; HC: Human capital; IC: Innovation capability; OP: Farmer-reported performance; TAR: Technology adoption readiness.

higher income, yield or profitability within the same production period. Even when farmers possess stronger financial resources, the outcome is still influenced by conditions beyond finance itself. Service reliability, output prices, weather, input costs and the fit between a technology and the household's land and labour situation all shape whether financial support can be converted into better results. In this respect, the finding is consistent with studies showing that rural credit is associated with technology adoption and scale-related efficiency in Chinese family farms (Cai et al. 2024; Wang et al. 2025). At the same time, it offers an important qualification: finance may create opportunities for adoption and adjustment, but it should not be viewed as an independent or automatic pathway to performance improvement.

Human capital follows a related but more cognitive route. Education, training, farming experience and management experience can help farmers understand advice, compare service options and judge whether a practice is manageable. The results point to a practical boundary: knowledge is not automatically usable. It may remain difficult to turn into short-term performance when plots are fragmented, seasonal labour is tight, services are unavailable or adjustment costs are high. The finding supports training and demonstration research, but it narrows the practical implication of such support: knowledge-based support may first be visible in readiness and judgement rather than in immediate performance indicators (Mgendi et al. 2022; Schulz and Börner 2023).

The innovation-capability result helps define the boundary of dynamic capability in smallholder farming. Innovation capability was linked to technology adoption readiness but not directly to farmer-reported performance, and the IC-only indirect paths were not supported. This is consistent with the view that technological change in smallholder agriculture is practical and locally embedded (Glover et al. 2019; Jalotjot and Tokuda 2024), while also qualifying firm-centred dynamic capability logic. In this setting, adaptive capability is less a formal routine for organisational reconfiguration than a household-level capacity to try, compare and adjust under land, labour, service and seasonal constraints. It may help farmers identify which practices are workable under local constraints, but its value becomes more visible when it is connected to readiness for a feasible technology. This also aligns with China-focused innovation-systems research, which shows that smallholder modernisation depends on how knowledge, services and local coordination are organised around farm households (Chen et al. 2024).

Technology adoption readiness was the construct most closely associated with farmer-reported performance in the model. This result should be read carefully. Readiness is not actual adoption, and the study does not observe whether farmers later used a technology or sustained its use over time. The result is better read in a limited sense. Readiness does not mean that a household has already adopted a technology, nor does it guarantee better performance. Instead, it suggests that the household may be nearer to a workable adjustment. When farmers perceive a technology as useful and manageable, they may already have a clearer understanding of its costs, feel fewer adoption barriers or have some access to the services required for trial use. This interpretation is consistent with studies on smart

farming and technology adoption, which regard perceived usefulness, intention, complexity and actual use as related but distinct elements in the adoption process (Cimino et al. 2024; Giua et al. 2022). Even so, readiness alone cannot account for farmer-reported performance. The R^2 values remain modest, and the predictive results for farmer-reported performance are weak. Farm outcomes continue to depend on many conditions outside the model, including machinery-service quality, market access, crop choice, land conditions, household labour allocation and production risk.

Theoretical and Practical Implications

The findings offer several implications for rural management research. The first concerns the resource-performance logic within the resource-based view. In this study, financial and human capital should not be interpreted as unimportant. Rather, the results point to a more specific conclusion: these resources are more closely associated with innovation capability and technology adoption readiness than with farmer-reported performance in a direct sense. For smallholder farming, therefore, the value of resources lies less in their possession alone and more in whether households can convert them into workable judgement and readiness to act. A second implication concerns the boundary of dynamic capability theory for smallholders. In this empirical setting, adaptive capability is not mainly found in formal routines, specialised departments or codified reconfiguration processes. It is carried through the household-service interface. Farmers may test a cultivation method on a small scale, compare machinery service options, adjust planting decisions from one season to another and decide whether external support can actually be put to use. This means that dynamic capability, in smallholder farming, is better understood as situated household adjustment under service-market, labour and land-fragmentation constraints, rather than as a bundle of firm-internal routines. A further implication is the need to keep innovation capability and technology adoption readiness conceptually separate. Innovation capability refers to a broader ability to experiment, compare and adjust. Technology adoption readiness is narrower and more technology-specific. It reflects the farmer's judgement that a feasible technology is useful, manageable and worth using when farm and service conditions make its use possible. The practical implications are centred on conversion rather than provision alone. Rural support programmes may be less useful when credit, training and technology promotion are delivered as separate interventions. Credit support could be linked with simple cost, risk and repayment assessments for specific technologies or production practices. Training programmes could give more attention to farmers' ability to compare service options, judge technology-land-labour fit and recognise the conditions under which a practice is manageable. Technology promotion could also be paired with demonstration plots, transparent machinery-service pricing and follow-up guidance after the first trial. These measures do not guarantee better performance, but they may reduce the gap between the resources available to farmers and their ability to assess, test and use feasible agricultural technologies when conditions allow.

Limitations and Future Research

Several limitations should be noted. The cross-sectional design supports claims about associations only, not causal or temporal relationships, and possible reverse relationships cannot be excluded. Farmer-reported performance was based on respondents' own evaluations and may be influenced by recall, local comparison or common-method bias. Technology adoption readiness represents a pre-adoption orientation rather than actual technology use. Although the sample included different parts of Henan, it was obtained through field access and should not be treated as a probability sample. Financial and human capital were measured as perceived reflective constructs and therefore do not fully capture objective differences across households. Future research could combine perceived measures with records on credit, savings, education, training, farm operations and performance. Longitudinal, experimental or seasonal follow-up designs would help distinguish readiness, trial use, sustained adoption and verified outcomes, while also incorporating service quality, market conditions, land characteristics, labour allocation, crop choice and production risk.

Conclusion

The overall pattern is clear. Financial and human capital were more closely related to innovation capability and technology adoption readiness than to farmer-reported performance. Their direct relationships with performance were not statistically supported. Innovation capability was associated with technology adoption readiness, but not directly with farmer-reported performance. Technology adoption readiness was the construct most closely linked to farmer-reported performance. This study therefore treats resource conversion as a useful lens for rural management. In household-based farming, finance and knowledge do not create value merely because they are available. They become useful when farmers can draw on them to make practical judgements, adjust production decisions and become better prepared to adopt feasible technologies.

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Authors' Contributions

Ke Li: Conceptualisation, methodology, data collection, formal analysis, writing – original draft and writing – review and editing.

Kartinah Ayupp: Supervision, conceptual guidance, methodology review and writing – review and editing.

All authors approved the revised manuscript and agree to be accountable for the work.

Author Responsibility Statement

All authors have read and approved the revised manuscript and agree to be accountable for all aspects of the work.

Consent to Participate

Informed consent to participate was obtained from all respondents before the survey interview. Consent was obtained verbally because the survey was conducted through face-to-face field interviews and no directly identifying personal information was collected.

Consent for Publication

Not applicable. The manuscript does not contain individual-level identifying details, images or videos.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request, subject to ethical and privacy considerations.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

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Appendix A: Measurement Items and Sources

Construct	Codes	Item	Source
Financial capital	FC1	I can obtain low-interest loans from local banks or rural credit cooperatives to support agricultural production	Cai et al. (2024), Khattak and Shah (2020), Wang et al. (2025)
	FC2	I can quickly access loans through informal channels, such as relatives or cooperatives, in urgent financial need	
	FC3	My household savings can sustain agricultural operations for at least 6 months during periods of financial fluctuation	
	FC4	I adopt risk-mitigation strategies such as agricultural insurance or diversified cropping	
Human capital	HC1	My formal education has given me the requisite skills and knowledge for effective agricultural management	Mgendi et al. (2022), Schulz and Börner (2023), Vidotto et al. (2017)
	HC2	Participation in specialised agricultural training has enhanced my practical competencies for farm operations	
	HC3	My work experience in agriculture aligns well with the current operational demands of my farming activities	
	HC4	My managerial experience in agriculture informs my decision-making and contributes to operational efficiency	
Innovation capability	IC1	During crop production, I am willing to experiment with innovative cultivation methods	Jalotjot and Tokuda (2024), Moreira et al. (2024)
	IC2	I have actively improved my farming processes over the past few years	
	IC3	I believe that adopting new cultivation management practices can enhance profits	
	IC4	In crop production, I can keenly perceive changes in market demand and adjust my planting strategies accordingly	

(Appendix A continued)

(Appendix A continued)

Construct	Codes	Item	Source
Technology adoption readiness	TAR1	I believe that using new agricultural technologies can enhance my income	Chau and Hu (2002), Cimino et al. (2024), Davis (1989), Giua et al. (2022), Venkatesh et al. (2003)
	TAR2	Integrating new agricultural technologies into my existing production processes is straightforward	
	TAR3	I intend to increase my use of new agricultural technologies within the next 1–2 years	
	TAR4	I will actively adopt new agricultural technologies whenever possible to improve my farm operations	
Farmer-reported performance	OP1	In 2023, the growth rate of my total crop income exceeded the village average	Latruffe et al. (2016)
	OP2	In 2023, the yield of my core crops per unit area improved compared to 2022	
	OP3	In 2023, the production profit margin of my core crops exceeded the village average	
	OP4	In 2023, the net profit per unit area of my core crops improved compared to 2022	

Journal Indexing Source Record

Frontiers in Sociology

Scopus; Web of Science Emerging Sources Citation Index (ESCI)

Source: Frontiers journal information

<https://www.frontiersin.org/journals/sociology/about>

Business Management and Strategy

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Sources: publisher indexing list and RePEc journal record

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International Journal of Rural Management

Scopus

Source: SAGE list of Scopus-indexed India journals

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Accessed: 23 September 2026

Source summary prepared for the nomination attachment.