

Training-to-application gaps in digital agricultural practices: Exploratory evidence from agricultural actors in China

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Abstract: Digital-skills training is increasingly used to advance agricultural digitalisation; however, participation and learning do not necessarily translate into application within production and business routines. This exploratory study investigates the training-to-application gap using 156 questionnaire records from agricultural actors in China recruited via convenience sampling through WeChat-based networks. The outcome is a broad, self-reported, four-category indicator of post-training digital application based on retrospective assessments of training experiences over the preceding two years, rather than a technology-specific measure of adoption, sustained use, or performance. Grounded in training-transfer theory, the analysis examines whether perceived content relevance, an inverse scenario/practice-barrier index, and course-linked post-training support are associated with higher reported application. Cumulative-logit estimates yielded no statistically detectable associations for the three indicators in the baseline model (likelihood-ratio test $p = .995$; McFadden pseudo- $R^2 = .001$). The conclusions concerning H1–H3 remained unchanged across alternative predictor coding, separate modelling of the two barrier components, and expanded covariate adjustment. An exploratory secondary finding indicated higher reported application among production-oriented respondents than among market- or service-oriented respondents; however, the broad outcome may not be fully comparable across business contexts. The study's principal contribution lies in conceptually distinguishing training participation, learning, initial trial, continued use, routinisation, and operational value. On this basis, the article advances a literature-informed Conditional Conversion Framework for future testing, in which technical feasibility, economic viability, platform and market fit, and ecosystem implementation support may enable or constrain progression across application stages.

Keywords: agricultural actors; agricultural extension; digital agriculture; post-training application; technology adoption; training transfer

1. Introduction

Digital agriculture comprises not a single technology but an evolving constellation of devices, software, data practices, platforms, advisory arrangements, and organisational routines deployed across production and farm-related business activities. It encompasses sensor-based monitoring, decision-support applications, digital record-keeping, e-commerce, traceability, online customer engagement, and data-informed service provision. Smart farming and precision agriculture constitute an important yet more technology-specific subset of this broader domain, typically referring to identifiable systems such as automated irrigation, variable-rate equipment,

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drones, robotics, or integrated data platforms. Because the present survey asks broadly whether respondents applied skills acquired through training and does not identify a particular technology, the empirical outcome is termed post-training digital application rather than smart-farming adoption. This distinction is essential because awareness, experimentation, continued use, and demonstrable operational benefit represent analytically distinct outcomes and should not be conflated within a single adoption claim (Klerkx et al., 2019; McGrath et al., 2023; Wolfert et al., 2017).

The practical potential of agricultural digitalisation depends on substantially more than technological availability. Data may facilitate more timely decision-making and reduce information asymmetries, but such benefits require users to embed digital tools within recurrent work practices. A mobile application may be opened once without becoming part of a production cycle; a spreadsheet may be mastered during a course yet abandoned when records remain incomplete; and an online sales account may be created without developing into a stable business process. Agricultural digitalisation is therefore more appropriately conceptualised as a socio-technical transformation in which technical systems interact with skills, institutions, and the material conditions of farming (Rijswijk et al., 2021; Rose & Chilvers, 2018; van der Burg et al., 2019). This perspective cautions against the assumption that increased training provision will automatically generate greater application.

The central analytical concern of this study is training transfer. Transfer-of-training research differentiates participation from learning, generalisation to the target setting, maintenance over time, and subsequent performance outcomes. Baldwin and Ford (1988) established this distinction by locating transfer in the generalisation and maintenance of trained knowledge and skills, as shaped by trainee characteristics, training design, and the work environment. Subsequent reviews have reinforced that instructional exposure is only the initial stage of a process whose later phases depend on motivation, content validity, realistic practice, and environmental support (Bell et al., 2017; Blume et al., 2010; Burke & Hutchins, 2007; Grossman & Salas, 2011). Agricultural training should therefore be evaluated not only through attendance or satisfaction, but also through the extent to which acquired capabilities are attempted, adapted, and maintained within heterogeneous operating contexts. This transfer perspective also requires a distinction between the absence of a statistically detectable association and evidence that a training condition is practically irrelevant; alternative mechanisms must be measured directly rather than inferred from nonsignificant coefficients (Lakens, 2017).

Training-transfer theory provides the primary foundation for H1–H3. Complementary acceptance and diffusion perspectives highlight usefulness, facilitating conditions, compatibility, and trialability (Davis, 1989; Venkatesh et al., 2003; Rogers, 2003). Agricultural adoption research adds profitability, risk, resources, and institutional context (Feder et al., 1985; Foster & Rosenzweig, 2010), while precision-agriculture reviews emphasise expected returns, complexity, advisory support, and compatibility (Barnes et al., 2019; Lowenberg-DeBoer & Erickson, 2019; Pierpaoli et al., 2013; Tey & Brindal, 2012). These perspectives contextualise application without replacing the focus on transferring capabilities acquired through training.

Responsible digitalisation adds attention to access, data governance, autonomy, and the distribution of benefits. Platform and equipment providers may shape interoperability and users' choices, while unequal connectivity and services may constrain application (Bronson & Knezevic, 2016; Rotz et al., 2019; Klerkx & Rose, 2020; van der Burg et al., 2019). These complementary considerations inform the prospective framework rather than additional hypotheses tested here.

Agricultural advisory systems provide a further complementary perspective: advisors and other providers help users interpret data, troubleshoot technologies, and integrate tools into workflows (Eastwood et al., 2019; Fielke et al., 2020; Ingram & Maye, 2020). Course-linked

follow-up is one part of this wider system; sustained application may also require maintenance, finance, logistics, or specialised advice.

China provides a relevant and rich context in which to examine these issues, as digital tools are being deployed across agricultural production, rural services, platform commerce, and entrepreneurship. Evidence on digital extension in China suggests that access to digital information may be associated with technology adoption, although effects vary across users and implementation contexts (Mao et al., 2024). Research on agricultural digital transformation in China similarly models interacting incentives and barriers among farmers, enterprises, and government actors rather than assuming a simple linear transition (Sun et al., 2024). Small farmers' intentions to adopt agricultural platforms are likewise shaped by user perceptions and ecosystem conditions (Cimino et al., 2024). Collectively, these studies affirm the relevance of digital capability while leaving unresolved the narrower transfer question examined here: whether respondents' perceptions of training relevance, scenario and practice barriers, and course-linked follow-up are associated with their reported post-training application.

The sample is deliberately characterised as comprising agricultural actors rather than 'new farmers'. The records include family-farm and cooperative leaders, agricultural-enterprise managers, returnee entrepreneurs, grassroots technicians, and ordinary farmers engaged in crop production, livestock and aquaculture, e-commerce, rural tourism, and agricultural services. These roles differ in their proximity to production, access to equipment and records, and the tasks to which digital skills may be applied. Such heterogeneity is analytically valuable for exploring variation across business contexts, but it also introduces a measurement challenge: an identical response category may denote substantively different activities in production, commerce, tourism, or service provision. The study therefore examines business-type heterogeneity explicitly and does not assume that the outcome carries an invariant substantive meaning across all groups.

The analysis focuses on three training-supply indicators because each corresponds to a proximal condition in transfer theory and is, at least in principle, amenable to intervention by training providers. Perceived content relevance captures the extent to which instruction appears aligned with operational needs. The inverse scenario/practice-barrier index indicates whether respondents did not select two specified problems: detachment from production or business scenarios and insufficient hands-on practice. Course-linked post-training support captures the reported availability of follow-up provision, including online question-and-answer services, return visits, or advanced courses. The study therefore tests whether this restricted set of observed indicators is associated with an ordered self-report of post-training application.

The study offers four contributions. First, it aligns the empirical outcome more closely with its measurement by reframing it from technology-specific smart-farming adoption to broad post-training digital application. Second, it situates the analysis within training-transfer theory and derives three directional hypotheses prior to examining the results. Third, it strengthens statistical transparency through comprehensive reporting, including the complete outcome distribution, proportional-odds diagnostics, odds ratios, thresholds, and multicollinearity checks. Furthermore, it assesses sensitivity to categorical predictor coding and expanded adjustment for observed heterogeneity. Fourth, it develops a Conditional Conversion Framework as a literature-informed agenda for future measurement rather than as an explanation inferred from null coefficients. The framework differentiates exposure, learning, initial trial, continued use, routinisation, and operational value, and proposes that progression may depend on configurations of technical feasibility, economic viability, platform and market fit, and ecosystem implementation support.

Accordingly, the article addresses the following question through three a priori hypotheses: are perceived training-content relevance, fewer reported scenario- and hands-on-practice barriers, and stronger course-linked post-training support positively associated with higher

reported post-training digital application? The analysis is exploratory and associational. It assesses whether the expected relationships are statistically detectable in this sample and whether the resulting conclusions remain stable under alternative coding and covariate adjustment. The analysis evaluates associations and their robustness rather than causal effects or unmeasured mechanisms.

2. Materials and Methods

2.1 Study design, recruitment, and respondents

The study employed an online questionnaire design. The analytical export comprised 156 completed records, and the source field identified WeChat for each retained case. Recruitment was non-probability-based: the questionnaire link was circulated through WeChat networks associated with agricultural production, business, training, and service activities. This design is appropriate for exploratory association testing; however, recruitment through WeChat is likely to favour people with smartphone and internet access, familiarity with digital communication, and connections to training networks. Actors with lower baseline digital literacy or limited connectivity may therefore be underrepresented. Pre-training digital literacy was not measured, so the extent and consequences of this selection cannot be quantified from the available data. For descriptive purposes, the approximate provincial-level distribution of the final analytical records, derived from platform IP metadata, is presented in Appendix Table A1; these locations should not be interpreted as verified residence or farm locations or as a sampling frame.

Eligibility was operationalised from the questionnaire structure and the retained records. Respondents were adults who identified with an agriculture-related role, reported a business domain connected to agricultural production or related services, and selected at least one category indicating participation in digital-skills training during the preceding two years. Eligible roles included family-farm or cooperative leaders, agricultural-enterprise managers, returnee youth entrepreneurs, grassroots agricultural technicians, and ordinary farmers. Eligible business domains comprised crop production, livestock and aquaculture, agricultural e-commerce and livestreaming, rural tourism or homestay operations linked to agriculture, and agricultural socialised services. Technicians, tourism operators, and service providers were included because the empirical focus encompassed farm-related digital application beyond direct cultivation.

The questionnaire included items on basic digital operations, agricultural applications and platforms, Internet of Things devices, online sales, data-analysis tools, training frequency, perceived training relevance, post-training application, reasons for unsatisfactory training outcomes, follow-up support, desired skills, preferred training formats, incentives, and desired continuing support. The focal model includes only variables corresponding to the stated training-transfer hypotheses and baseline controls. Other questionnaire items were excluded because they measure current digital skills, preferences, or desired services rather than the selected training-supply conditions.

All substantive variables were self-reported. Participation was voluntary, and the questionnaire requested neither names nor national identification numbers or farm addresses. The survey involved adults and concerned training and work practices. The sample was intentionally heterogeneous. Production-oriented actors may have direct opportunities to use monitoring, record-keeping, or input-management tools, whereas market- and service-oriented actors may apply digital skills through platform operations, customer communication, logistics, or advisory activities. This diversity broadens the practical domain examined but weakens the assumption that a single broad application item is measurement-invariant across groups. Accordingly, the analysis reports nonparametric group comparisons and robustness models adjusted for business orientation, operating scale, identity, and gender. These analyses address observed heterogeneity without treating the controls as a complete causal model. No values

were missing for the outcome, the three focal indicators, age, training frequency, gender, identity, business type, or operating scale in the 156-record analytical export.

2.2 Training-transfer framework and a priori hypotheses

Training effectiveness unfolds across conceptually distinct stages. Exposure denotes attendance at or access to instruction; learning refers to changes in knowledge, skills, or attitudes; transfer concerns application in a target setting; maintenance refers to continued use; and performance encompasses operational or economic outcomes. A course may produce learning without transfer, transfer without long-term maintenance, or continued use without measurable benefit. Baldwin and Ford's (1988) framework remains foundational because it links transfer to trainee characteristics, training design, and the work environment. Subsequent scholarship has refined these domains and shown that motivation, content validity, practice design, opportunities to perform, supervisor or peer support, and follow-up may influence whether trained capabilities are generalised and maintained (Bell et al., 2017; Blume et al., 2010; Burke & Hutchins, 2007; Grossman & Salas, 2011).

The study examines three proximal indicators available in the questionnaire: perceived content relevance, an inverse index of two scenario/practice barriers, and course-linked post-training support. The hypotheses concern their expected associations with reported application; alternative socio-technical conditions are considered after the empirical analysis as directions for future testing.

2.2.1 Training-content relevance

Content relevance denotes the perceived correspondence between instruction and the tasks, problems, and decisions encountered in the intended application environment. Within the Learning Transfer System Inventory, perceived content validity captures the extent to which trainees regard course content as reflecting actual performance requirements (Holton et al., 2000). Relevance may influence transfer through motivational and cognitive pathways. When trainees perceive a clear connection between instruction and operational needs, they may be more willing to invest effort in initial application. Alignment may also reduce the reinterpetive work required to map generic knowledge onto a concrete task.

This mechanism is particularly plausible in agriculture because work is temporally, materially, and contextually situated. A digital record-keeping procedure may need to align with a crop cycle, animal-management routine, traceability requirement, or sales workflow. Generic examples can leave participants uncertain about when to use a tool, which data to enter, and how to interpret its outputs. By contrast, content anchored in recognisable tasks can provide a clearer use case and narrow the cognitive distance between classroom instruction and field application. Training reviews consistently identify meaningful content, transfer motivation, and alignment with job requirements as relevant to subsequent use (Gegenfurtner et al., 2009; Grossman & Salas, 2011).

In this study, relevance is treated as a perceived rather than independently verified correspondence between course content and operational needs. H1: Greater perceived training-content relevance is positively associated with a higher level of reported post-training digital application.

2.2.2 Scenario and practice barriers

Transfer is more likely when training provides cues, procedures, and practice conditions that resemble the target environment. Realistic tasks can facilitate procedural knowledge and increase the likelihood that relevant knowledge will be retrieved when similar problems arise after training. Opportunities for practice can also reveal implementation difficulties while instruction or feedback remains available. Across the training literature, behavioural practice,

error management, realistic environments, and active learning have been associated with transfer-related outcomes, although their effects vary across tasks and contexts (Bell et al., 2017; Blume et al., 2010; Grossman & Salas, 2011).

Digital application in agriculture is highly context-dependent. The meaning of a dashboard varies with the crop or animal, production stage, and quality of the underlying data. Platform procedures depend on channel rules and customer expectations, while data-analysis techniques depend on whether records are complete and connected to operational decisions. Training detached from these conditions may leave participants with declarative knowledge but no workable sequence of action. Hands-on practice may narrow this gap by allowing participants to rehearse data entry, device operation, interpretation, or platform tasks using examples that resemble their own work. The resulting indicator captures the absence of two reported barriers rather than a validated multidimensional measure of contextual embeddedness. H2: Fewer reported barriers related to scenario detachment and insufficient hands-on practice are positively associated with a higher level of reported post-training digital application.

2.2.3 Course-linked post-training support

Transfer extends beyond the conclusion of formal instruction. During initial use of a new procedure, participants may encounter forgotten steps, unexpected data requirements, software incompatibility, device malfunction, or uncertainty about how to interpret results. Timely feedback and assistance may reduce the costs of experimentation and prevent remediable problems from resulting in abandonment. Training-transfer research accordingly identifies opportunities to perform, feedback, supervisor or peer support, and transfer climate as relevant post-training conditions (Burke & Hutchins, 2007; Chiaburu & Marinova, 2005; Holton et al., 2000).

Follow-up may be especially consequential in digital agriculture because technical and agronomic questions are frequently intertwined. A software problem may impede data entry; weak connectivity may interrupt a sensor; and an output may be technically correct yet agronomically difficult to interpret. Advisory research indicates that digital tools can transform advisors' work by increasing the importance of data interpretation, technology assessment, and coordination among farmers and technology providers (Eastwood et al., 2019; Fielke et al., 2020). Course-linked support, including online question-and-answer services, return visits, or advanced courses, may therefore assist participants during the early application period.

The observed item captures perceived course-linked follow-up rather than the wider agricultural implementation ecosystem. H3: Greater availability of course-linked post-training support is positively associated with a higher level of reported post-training digital application. The hypothesised relationships among the training-transfer indicators and post-training digital application are illustrated in Figure 1, and the theoretical basis and proposed mechanisms underlying H1–H3 are summarised in Table 1.

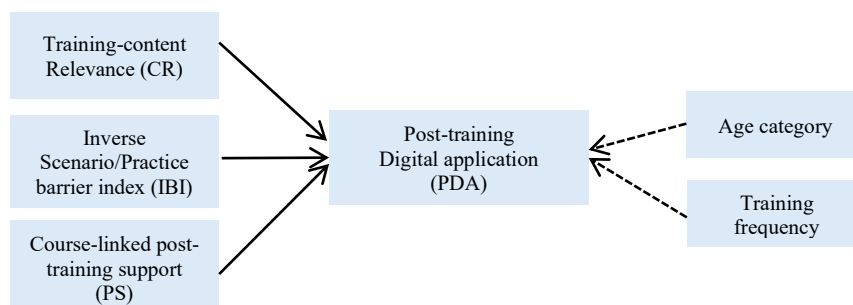


Figure 1. Hypothesised training-transfer model of post-training digital application.

Note: Solid arrows represent the three a priori hypothesised associations. Dashed arrows represent statistical controls. The arrows denote expected associations rather than causal effects.

Table 1. Theoretical derivation of the training-transfer hypotheses.

Training-supply indicator	Transfer-theory domain	A priori mechanism	Hypothesis
Perceived training-content relevance	Training design and content validity	Alignment with operational needs may enhance perceived utility and reduce the distance between instruction and target tasks.	H1
Inverse scenario/practice-barrier index	Transfer design and contextual correspondence	Fewer reported scenario- and hands-on-practice barriers may indicate more usable task cues and greater procedural rehearsal.	H2
Course-linked post-training support	Immediate post-training application environment	Follow-up assistance and feedback may alleviate early implementation difficulties and facilitate application.	H3

Note: The table presents only the a priori rationales. Alternative technical, economic, platform, market, and institutional explanations were not measured in the baseline model and are considered later as directions for future research.

2.3 Measures and variable coding

The original questionnaire was administered in Chinese. Although the analytical export retained only the Chinese item headings and numerical response codes, the wording of the original response options was verified against the archived questionnaire-platform version. Table 2 therefore provides close English translations of the original items and response options together with their analytical coding.

The training block began with a question asking how many digital-skills courses organised by government agencies, vocational institutions, or training providers the respondent had attended during the preceding two years. Subsequent items referred to ‘the training attended’ and ‘after training’ without identifying the most recent or most important course. CR, IBI, PS, and the outcome are therefore interpreted as overall retrospective assessments of respondents’ training experiences during that two-year period. Respondents who attended multiple courses may have averaged across experiences, selected a particularly salient course, or used different reference events. This ambiguity may have weakened alignment between the predictors and the outcome. In particular, averaging ratings across courses with different content, support, and opportunities for use may obscure course-specific relationships and attenuate the associations tested in H1–H3. Recall error and inconsistent reference events may also introduce bias; its direction and magnitude cannot be established from these data. Accordingly, the estimates should be interpreted as associations between respondents’ overall retrospective training assessments and reported digital application, rather than as course-specific relationships. The conclusions concerning H1–H3 remained unchanged across alternative coding and covariate specifications, although these checks do not eliminate potential measurement bias.

The dependent variable is post-training digital application (PDA), corresponding to the original analytical code SC. The Chinese item asked: ‘After the training, how did you apply the skills learned in actual production/operation?’ Responses were coded into four ordered categories from 1 to 4, with higher codes indicating greater reported application. PDA is a broad, single-item outcome. It does not identify the technology used, the task performed, the duration or frequency of use, whether application represented an initial trial or continued routine, or whether it generated operational value. It should therefore not be construed as a validated transfer scale, nor as direct evidence of adopting a specified smart-farming system.

Training-content relevance (CR) was measured by an item asking how closely the training content matched the respondent’s actual needs. Responses were coded from 1 to 5, with higher values indicating stronger perceived alignment. The item provides a global evaluation and does not compare the curriculum with independently observed job tasks. As a single-item measure, it cannot support an estimate of internal consistency or distinguish among dimensions of relevance such as level, topic, timing, and task specificity.

The inverse scenario/practice-barrier index (IBI) was constructed from two binary options in the multiple-response question concerning reasons for unsatisfactory training outcomes. B1 was coded 1 when ‘training content was detached from actual production/business scenarios’ was selected and 0 otherwise. B2 was coded 1 when ‘the training format was lecture-only and lacked hands-on practice’ was selected and 0 otherwise. IBI was calculated as $2 - (B1 + B2)$, yielding values from 0 to 2. A score of 0 indicates that both barriers were selected, 1 that one barrier was selected, and 2 that neither was selected. Higher values therefore denote fewer reported barriers rather than demonstrated positive embeddedness.

Course-linked post-training support (PS) was measured by an item asking whether follow-up was provided after training, with examples including online question-and-answer support, return visits, and advanced courses. The export contains four ordered codes, analysed from no or the lowest level of support to extensive or the highest level of support. Despite the grammatical form of the Chinese question, the item is not binary. It does not distinguish among support providers, content, accessibility, duration, responsiveness, or use, and it is considerably narrower than the ecosystem implementation support proposed later in the article.

Age was coded as 1 = 18-30 years, 2 = 31-45 years, 3 = 46-55 years, and 4 = 56 years or above. Training frequency was coded into three ordered categories representing increasing participation during the preceding two years; the analytical descriptors are once, two or three times, and four times or more. Gender, identity, business type, and operating scale were used in descriptive or robustness analyses. Business type was additionally recoded into production-oriented activities (crop production; livestock and aquaculture) and market- or service-oriented activities (e-commerce/livestreaming; rural tourism/homestay; agricultural socialised services).

These indicators should be interpreted as specific recorded measures rather than comprehensive scales of training design, transfer climate, or sustained digital practice. Their broad and partly retrospective nature may attenuate associations and limit comparability across application contexts (Diamantopoulos et al., 2012).

Table 2. Survey items, reference frame, analytical labels, coding, and interpretation.

Variable	Survey item and reference frame	Analytical labels and coding	Interpretation
Post-training digital application (PDA; original code SC)	“After the training, how did you apply the skills learned in actual production/operation?” Overall retrospective assessment of training during the previous two years.	1 = no application; 2 = limited application; 3 = moderate application; 4 = extensive application.	Higher values indicate greater broad self-reported application, not technology-specific adoption, duration, routinisation, or performance.
Training-content relevance (CR)	“How well did the training content match your actual needs?” Overall retrospective assessment.	1 = not matched at all; 2 = poorly matched; 3 = moderately matched; 4 = well matched; 5 = very well matched.	Higher values indicate stronger perceived matching.
Inverse scenario/practice-barrier index (IBI)	Selection of scenario detachment (B1) and lecture-only/no hands-on practice (B2) among reported barriers.	$IBI = 2 - (B1 + B2)$; 0 = both selected; 1 = one selected; 2 = neither selected.	Higher values indicate fewer of the two reported barriers, not validated contextual embeddedness.
Course-linked post-training support (PS)	“After training, was there follow-up such as online Q&A, return visits, or advanced courses?” Overall retrospective assessment.	1 = no/lowest follow-up; 2 = limited; 3 = moderate; 4 = extensive/highest.	Higher values indicate greater reported course-linked follow-up; the type and quality of support are not differentiated.
Age category	“What is your age group?”	1 = 18-30; 2 = 31-45; 3 = 46-55; 4 = 56 or above.	Higher values indicate older categories.
Training frequency	“During the previous two years, how many organised digital-skills training courses did you attend?”	1 = once; 2 = two or three times; 3 = four times or more.	Higher values indicate more frequent participation.

Note: The English wording of the items and response options represents close translations verified against the archived Chinese questionnaire. Numerical coding follows the original questionnaire-platform settings.

2.4 Statistical analysis

The analysis first reported frequencies and percentages for each category of the ordinal outcome. The median and interquartile range were emphasised because PDA is ordinal rather than interval-scaled; the mean and standard deviation were also reported for descriptive purposes. Sample characteristics were summarised as counts and percentages. Differences across identity and business-type groups were assessed using Kruskal-Wallis tests, and the production-versus-market/service comparison employed a Mann-Whitney test. These nonparametric procedures compare ordered distributions without assuming equal distances between outcome categories.

Cumulative-logit ordered logistic regression was used because PDA comprises four ordered categories (McCullagh, 1980). The model estimates common cumulative odds of occupying a higher rather than a lower outcome category. Positive coefficients and odds ratios greater than 1 indicate higher cumulative odds of reporting greater application. Results are presented as coefficients, standard errors, odds ratios, 95% confidence intervals, and two-sided p-values. The three thresholds separating adjacent cumulative divisions of the outcome are also reported. McFadden's pseudo- R^2 is interpreted as a likelihood-based comparative fit statistic rather than as the proportion of outcome variance explained.

The baseline model included CR, IBI, PS, age, and training frequency as ordered numerical scores. This parsimonious specification tests monotonic associations but assumes that each one-category increase exerts an equal effect on the log odds. Because the distances between ordinal categories may not be equivalent, all five predictors were re-estimated as sets of indicator variables in a sensitivity model. A likelihood-ratio comparison evaluated whether the categorical specification improved model fit, and joint Wald tests assessed each multi-category predictor.

As an additional sensitivity analysis, the two binary components of the inverse scenario/practice-barrier index were entered separately in place of the composite IBI score. The scenario-detachment barrier was coded 1 when the respondent selected "training content was detached from actual production or business scenarios" and 0 otherwise. The hands-on-practice barrier was coded 1 when the respondent selected "the training format was lecture-only and lacked hands-on practice" and 0 otherwise. This specification was used to assess whether aggregation into the inverse index concealed divergent associations between its two components and post-training digital application. All other predictors and controls were retained from the corresponding baseline and adjusted models.

The proportional-odds, or parallel-lines, assumption was evaluated using a Brant-type robust Wald procedure derived from cumulative binary logits (Brant, 1990). Global and variable-specific tests assessed whether slope estimates could be treated as constant across the three cumulative splits. The standard ordered-logit model was retained when the assumption was not rejected. Had variable-specific or global violations been detected, a partial proportional-odds or generalised ordered-logit specification would have been required (Williams, 2006).

Spearman rank correlations were used because the focal variables are ordinal or short discrete scores, while variance inflation factors provided an additional diagnostic of multicollinearity. The baseline model adjusted for age and training frequency. Robustness Model 2 added business orientation, and Model 3 additionally included operating scale, respondent identity, and gender as categorical controls. These models evaluate whether the focal estimates remain stable after observed heterogeneity is introduced; they do not constitute a complete causal adjustment set.

Model-based standard errors are reported in the main tables, with Huber-White HC0 sandwich standard errors calculated as a sensitivity check. Convergence was evaluated from optimiser status and the absence of warnings. The analytical file contained complete data for

all included variables; consequently, no imputation or listwise deletion beyond the supplied 156-record export was required. Statistical tests used a two-sided .05 threshold, although inference emphasised effect estimates and confidence intervals rather than a binary significant/nonsignificant classification.

All analyses were conducted in Python 3.13.5 using statsmodels 0.14.6, SciPy, and NumPy. Ordered-logit models were estimated by maximum likelihood with a logistic cumulative distribution and Broyden–Fletcher–Goldfarb–Shanno optimisation. The internally parameterised threshold estimates produced by statsmodels were transformed into ordered cumulative-logit cut-points before reporting.

3. Results and Discussion

3.1 Sample profile and outcome distribution

Table 3 presents the descriptive statistics and full distribution of PDA. The median outcome category was 2, with an interquartile range of 2–3. Limited application was the most frequent category, reported by 57 respondents (36.5%), followed by moderate application among 42 respondents (26.9%). A further 34 respondents (21.8%) reported no application, and 23 (14.7%) reported extensive application. Overall, 58.3% fell within the no- or limited-application categories, whereas 41.7% reported moderate or extensive application. Each category contained at least 23 observations, indicating no severe sparsity in the four-category outcome.

The mean PDA score was 2.346 (SD = 0.981), but this value is not interpreted as a precise location between categories. Substantive interpretation instead relies on category proportions, the median, and the interquartile range. This approach avoids assuming that the distance from no application to limited application is equivalent to that from moderate to extensive application, and it prevents a generic item from being misconstrued as evidence of adoption of a particular technology.

CR had a median of 3 and an interquartile range of 2–4, indicating substantial variation in perceived alignment. IBI was concentrated at 1: 109 respondents reported one of the two specified barriers, 18 reported both, and 29 reported neither. PS had a median of 2 and an interquartile range of 1–3. These distributions indicate that respondents were not uniformly negative about training; however, descriptive ratings alone cannot establish whether the indicators are associated with subsequent application.

Table 4 summarises the sample profile. Men accounted for 55.8% of respondents and women for 44.2%. The largest age group was 31–45 years (32.7%), followed by 18–30 years (25.0%), 46–55 years (24.4%), and 56 years or above (17.9%). Agricultural-enterprise managers constituted the largest identity category (32.1%), whereas e-commerce/livestreaming was the largest business category (29.5%). This diversity in identities, activities, and operating scales supports comparison but cautions against generalisation to a homogeneous farmer population.

Table 3. Descriptive statistics and distribution of post-training digital application (N = 156).

Panel A. Descriptive statistics of analytical variables						
Variable	Mean	SD	Median	Q1–Q3	Minimum	Maximum
Post-training digital application (PDA)	2.346	0.981	2	2–3	1	4
Training-content relevance (CR)	3.256	1.274	3	2–4	1	5
Inverse scenario/practice-barrier index (IBI)	1.071	0.546	1	1–1	0	2
Course-linked post-training support (PS)	2.308	1.045	2	1–3	1	4
Age category	2.353	1.046	2	1.75–3	1	4
Training frequency	2.090	0.790	2	1–3	1	3

Panel B. Distribution of post-training digital application

PDA code	Analytical response category	Frequency (N)	Percentage (%)
1	No application	34	21.8
2	Limited application	57	36.5
3	Moderate application	42	26.9
4	Extensive application	23	14.7
	Total	156	100.0

Note: Q1-Q3 denotes the first and third quartiles. The response descriptors are analytical English labels; see the measurement note in Table 2.

Table 4. Sample characteristics (N = 156).

Dimension	Category	Frequency (N)	Percentage (%)
Gender	Male	87	55.8
	Female	69	44.2
Age	18-30 years	39	25.0
	31-45 years	51	32.7
	46-55 years	38	24.4
	56 years or above	28	17.9
Identity	Family farm/cooperative leader	27	17.3
	Agricultural enterprise manager	50	32.1
	Returnee youth entrepreneur	33	21.2
	Grassroots agricultural technician	23	14.7
	Ordinary farmer	23	14.7
Business type	Crop production	31	19.9
	Livestock and aquaculture	38	24.4
	Agricultural e-commerce/livestreaming	46	29.5
	Rural tourism/homestay operation	22	14.1
	Agricultural socialised services	19	12.2
Operating scale	Small scale	36	23.1
	Medium scale	71	45.5
	Large scale	49	31.4

Note: Percentages are calculated from the 156-record analytical export and may not sum to 100.0 within dimensions because of rounding.

3.2 Variation across respondent and business groups

Because PDA is ordinal, Table 5 reports medians and interquartile ranges alongside means and standard deviations. The Kruskal-Wallis test detected no difference across the five identity categories, $H(4) = 1.114$, $p = .892$, and every identity group had a median of 2. Although returnee entrepreneurs and grassroots technicians displayed slightly higher means than some other groups, the ordered distributions overlapped extensively. The data therefore provide no evidence that identity category alone differentiates application in this sample.

Business type exhibited a different pattern. The Kruskal-Wallis test was statistically significant, $H(4) = 16.604$, $p = .002$. The median was 3 among crop-production respondents, 2.5 among livestock and aquaculture respondents, 2 among e-commerce/livestreaming respondents, 2 among agricultural-service respondents, and 1.5 among rural tourism/homestay respondents.

For a parsimonious robustness analysis, crop production and livestock/aquaculture were combined as production-oriented activities, whereas e-commerce/livestreaming, rural tourism/homestay, and agricultural socialised services were grouped as market- or service-oriented activities. The production-oriented group had a median PDA of 3, compared with 2 in the market- or service-oriented group. The Mann-Whitney comparison was statistically significant, $U = 3805.0$, $p = .003$.

This group pattern is an exploratory secondary finding rather than evidence that production orientation causes stronger transfer. Production-oriented actors may have more immediate opportunities to apply instrumental and task-bounded capabilities related to monitoring, record keeping, input management, or traceability. Market- and service-oriented actors may rely more heavily on relational, strategic, and adaptive capabilities whose application is less readily captured by the broad PDA item. The difference may therefore reflect both substantive variation

in conversion pathways and incomplete comparability of the outcome across business contexts. These possibilities are examined further in Section 3.5.

The finding also underscores the need for robustness checks on the baseline model. A null coefficient for a training indicator could be obscured or distorted if business context is associated both with perceptions of training and with opportunities to apply acquired skills. Models incorporating business orientation, operating scale, identity, and gender are therefore reported in Section 3.4.

Table 5. Post-training digital application across respondent groups.

Dimension	Group	N	Median	Q1–Q3	Mean	SD
Identity	Family farm/cooperative leader	27	2.0	2.0-3.0	2.222	0.974
	Agricultural enterprise manager	50	2.0	2.0-3.0	2.340	0.961
	Returnee youth entrepreneur	33	2.0	2.0-3.0	2.455	1.063
	Grassroots agricultural technician	23	2.0	2.0-3.0	2.435	1.037
	Ordinary farmer	23	2.0	1.5-3.0	2.261	0.915
Business type	Crop production	31	3.0	2.0-3.0	2.677	0.871
	Livestock and aquaculture	38	2.5	2.0-3.0	2.553	1.005
	Agricultural e-commerce/livestreaming	46	2.0	1.25-3.0	2.304	1.008
	Rural tourism/homestay operation	22	1.5	1.0-2.0	1.682	0.894
	Agricultural socialised services	19	2.0	2.0-3.0	2.263	0.806
Orientation	Production-oriented	69	3.0	2.0-3.0	2.609	0.943
	Market- or service-oriented	87	2.0	1.0-3.0	2.138	0.967

Note: Identity comparison: Kruskal-Wallis $H(4) = 1.114$, $p = .892$. Business-type comparison: $H(4) = 16.604$, $p = .002$. Orientation comparison: Mann-Whitney $U = 3805.0$, $p = .003$.

3.3 Model diagnostics, baseline estimates, and hypothesis testing

Spearman correlations between PDA and CR, IBI, and PS were all close to zero (Table 6). The largest absolute correlation among the baseline predictors was .169, observed between CR and training frequency. Variance inflation factors ranged from 1.016 to 1.056, providing no indication that substantial dependence among the included predictors destabilised the baseline coefficients.

The global Brant-type test did not reject the proportional-odds assumption, chi-square(10) = 5.762, $p = .835$. Variable-specific tests were likewise nonsignificant for CR, IBI, PS, age, and training frequency. The common-slope cumulative-logit specification was therefore retained. This diagnostic is substantively important because a violation would indicate that a predictor's association varies across the transitions separating lower from higher outcome categories.

Table 7 presents the focal estimates. No statistically detectable association was found between CR and PDA, $B = -0.021$, $OR = 0.979$, 95% CI [0.777, 1.233], $p = .857$; H1 was therefore not supported. IBI was also nonsignificant, $B = -0.065$, $OR = 0.937$, 95% CI [0.554, 1.585], $p = .809$, providing no support for H2. No statistically detectable association was found between PS and PDA, $B = -0.085$, $OR = 0.918$, 95% CI [0.695, 1.214], $p = .550$; H3 was not supported.

Age and training frequency were also nonsignificant. Relative to the intercept-only model, the predictor model produced only a marginal improvement in log likelihood: LR chi-square(5) = 0.426, $p = .995$. McFadden's pseudo- R^2 was .001. This value indicates negligible comparative improvement in model fit; it does not imply that 0.1% of the outcome variance was explained. The model converged without warnings, and the use of Huber–White HC0 sandwich standard errors did not alter the inferential conclusions.

In summary, these estimates indicate that the hypothesised associations were not detected under the available measures. Given the width of the confidence intervals and the exploratory design, these results do not warrant claims of equivalence or causality. The outcome thresholds, model-fit statistics, and proportional-odds diagnostics are summarised in Table 8.

Table 6. Spearman rank correlations and baseline variance inflation factors.

Variable	1	2	3	4	5	6	VIF
1. PDA	1.000						-
2. CR	-0.018	1.000					1.056
3. IBI	-0.010	-0.081	1.000				1.026
4. PS	-0.036	-0.091	-0.134	1.000			1.041
5. Age	0.012	0.071	-0.030	0.076	1.000		1.016
6. Training frequency	-0.011	0.169	0.043	-0.093	-0.029	1.000	1.041

Note: Entries are Spearman rank correlations. VIFs were calculated for the five baseline predictors; PDA is the dependent variable.

Table 7. Baseline ordered-logit estimates and hypothesis decisions.

Predictor	B	SE	OR	95% CI for OR	p	Decision
Training-content relevance (CR)	-0.021	0.118	0.979	[0.777, 1.233]	.857	H1 not supported
Inverse scenario/practice-barrier index (IBI)	-0.065	0.268	0.937	[0.554, 1.585]	.809	H2 not supported
Course-linked post-training support (PS)	-0.085	0.142	0.918	[0.695, 1.214]	.550	H3 not supported
Age category	0.017	0.140	1.017	[0.772, 1.340]	.903	-
Training frequency	-0.028	0.191	0.972	[0.669, 1.414]	.883	-

Note: Positive coefficients and odds ratios above 1 indicate higher cumulative odds of occupying a higher PDA category. “Not supported” denotes the absence of a statistically detectable association in the specified model.

Table 8. Outcome thresholds, model fit, and proportional-odds diagnostics.

Diagnostic	Result
Threshold 1 (category 1 vs 2-4)	-1.638
Threshold 2 (categories 1-2 vs 3-4)	-0.018
Threshold 3 (categories 1-3 vs 4)	1.406
Log likelihood	-208.116
Intercept-only log likelihood	-208.329
Likelihood-ratio test	chi-square(5) = 0.426, p = .995
McFadden pseudo-R ²	.001
AIC / BIC	432.232 / 456.631
Global Brant-type test	chi-square(10) = 5.762, p = .835
CR / IBI / PS tests	p = .384 / .580 / .159
Age / training-frequency tests	p = .969 / .997
Convergence	Achieved without warnings

Note: Thresholds are reported on the cumulative-logit scale. The proportional-odds assumption was not rejected either globally or for any baseline predictor.

3.4 Robustness and sensitivity analyses

The first robustness check relaxed the equal-step assumption imposed by numerical scoring of the ordinal predictors. CR, IBI, PS, age, and training frequency were represented by categorical indicators, with their lowest categories serving as reference groups. The categorical model did not fit significantly better than the score-coded model, LR chi-square(9) = 8.730, $p = .463$. Joint Wald tests were nonsignificant for CR, IBI, PS, age, and training frequency. The decisions concerning H1–H3 were therefore unchanged when category spacing was allowed to be non-linear.

When the two components of IBI were entered separately, neither the scenario-detachment barrier (OR = 0.987, 95% CI [0.522, 1.868], $p = .969$) nor the lack-of-hands-on-practice barrier (OR = 1.162, 95% CI [0.601, 2.247], $p = .656$) showed a statistically detectable association with PDA. The estimates for CR (OR = 0.986, 95% CI [0.781, 1.245], $p = .908$) and PS (OR = 0.917, 95% CI [0.694, 1.213], $p = .545$) remained materially unchanged from those in the

baseline model. The separate-component specification therefore provided no evidence that aggregation of the two barriers concealed a detectable component-specific association, and the decision concerning H2 remained unchanged.

Model 2 added the production-versus-market/service indicator. CR, IBI, and PS remained nonsignificant. Production-oriented respondents had higher cumulative odds of reporting a higher PDA category, OR = 2.460, 95% CI [1.359, 4.450], $p = .003$. This association is consistent with the nonparametric group comparison but remains observational.

Model 3 additionally incorporated operating scale, identity, and gender. The focal associations again were not statistically detectable: OR = 0.936 for CR, 1.003 for IBI, and 0.984 for PS. Production orientation remained associated with higher PDA, OR = 2.743, 95% CI [1.483, 5.072], $p = .001$. Operating scale and identity were not jointly significant, and gender was nonsignificant. The maximum VIF in the full model was 2.083, while the global proportional-odds test remained nonsignificant, $\chi^2(26) = 19.023$, $p = .835$.

The fully adjusted model was used to assess estimate stability rather than to maximise predictive fit. Overall, the focal conclusions were unchanged across predictor coding, the component-level IBI sensitivity analysis, and expanded covariate adjustment.

The production-orientation association remains exploratory. It may reflect variation in digitally tractable tasks, equipment, records, operating scale, market relationships, or interpretation of the broad outcome item. Activity-specific outcomes and measurement-invariance testing are required before the magnitude of this group difference can be interpreted substantively. The robustness and sensitivity estimates are summarised in Table 9.

Table 9. Robustness of focal ordered-logit estimates.

Panel A. Robustness across covariate specifications			
Variable or statistic	Model 1: baseline	Model 2: + orientation	Model 3: fully adjusted
CR, OR [95% CI]	0.979 [0.777, 1.233]	0.947 [0.749, 1.197]	0.936 [0.729, 1.203]
CR, p	.857	.650	.606
IBI, OR [95% CI]	0.937 [0.554, 1.585]	0.972 [0.574, 1.646]	1.003 [0.579, 1.736]
IBI, p	.809	.917	.992
PS, OR [95% CI]	0.918 [0.695, 1.214]	0.944 [0.713, 1.251]	0.984 [0.737, 1.313]
PS, p	.550	.690	.913
Production-oriented, OR [95% CI]	-	2.460 [1.359, 4.450]	2.743 [1.483, 5.072]
Production-oriented, p	-	.003	.001
Scale / identity joint p	-	-	.717 / .663
Gender p	-	-	.108
Log likelihood	-208.116	-203.589	-201.082
McFadden pseudo- R^2	.001	.023	.035
AIC / BIC	432.232 / 456.631	425.177 / 452.626	434.163 / 482.961
N	156	156	156

Note: Model 1 includes CR, IBI, PS, age, and training frequency. Model 2 adds business orientation. Model 3 additionally includes operating scale, respondent identity, and gender. Fully categorical coding of the five ordinal baseline predictors did not improve model fit, LR $\chi^2(9) = 8.730$, $p = .463$. Separating the two IBI components did not alter the decision concerning H2 (see Section 3.4).

Panel B. Sensitivity analysis separating IBI components			
Predictor	OR	95% CI	p
Training-content relevance	0.986	[0.781, 1.245]	.908
Scenario-detachment barrier	0.987	[0.522, 1.868]	.969
Lack-of-hands-on-practice barrier	1.162	[0.601, 2.247]	.656
Course-linked post-training support	0.917	[0.694, 1.213]	.545
Age category	1.018	[0.773, 1.341]	.900
Training frequency	0.966	[0.664, 1.407]	.858

Note: In Panel B, the two barrier indicators are coded 1 when the barrier was selected and 0 otherwise. Consequently, odds ratios above 1 indicate higher reported application among respondents selecting the barrier, which is opposite to the direction represented by the inverse composite IBI. Neither component showed a statistically detectable association.

3.5 Conditional Conversion Framework and Implications

The absence of statistically detectable associations for H1–H3 places limits on what can be concluded about the measured training conditions. Although the estimates were stable across specifications, their confidence intervals remained compatible with associations in either direction; the baseline interval for IBI, for example, ranged from 0.554 to 1.585. No equivalence test was conducted. These results do not establish equivalence or demonstrate that relevance, practice, and follow-up are unimportant. The sample and retrospective measures constrain inference, without identifying the reasons for the nonsignificant findings. Training-transfer theory nevertheless provides a basis for considering how acquired capabilities may become embedded in agricultural work. Drawing on this literature and complementary research on agricultural digitalisation, the Conditional Conversion Framework in Figure 2 distinguishes stages of application and the conditions that may shape progression between them. It is a conceptual synthesis for future empirical testing.

The framework separates training exposure and learning from initial trial, continued use, routinisation, and operational or economic value. This distinction extends the transfer literature's emphasis on generalisation and maintenance in the target setting (Baldwin & Ford, 1988; Bell et al., 2017; Burke & Hutchins, 2007). A participant may acquire a skill without having an opportunity to attempt it, while an initial attempt may be discontinued before it becomes part of a recurring workflow. Even routine use may yield little benefit when its costs exceed its contribution to decisions or operations. The analytical value of separating these stages lies in recognising that the conditions supporting an initial attempt may differ from those supporting sustained and beneficial application.

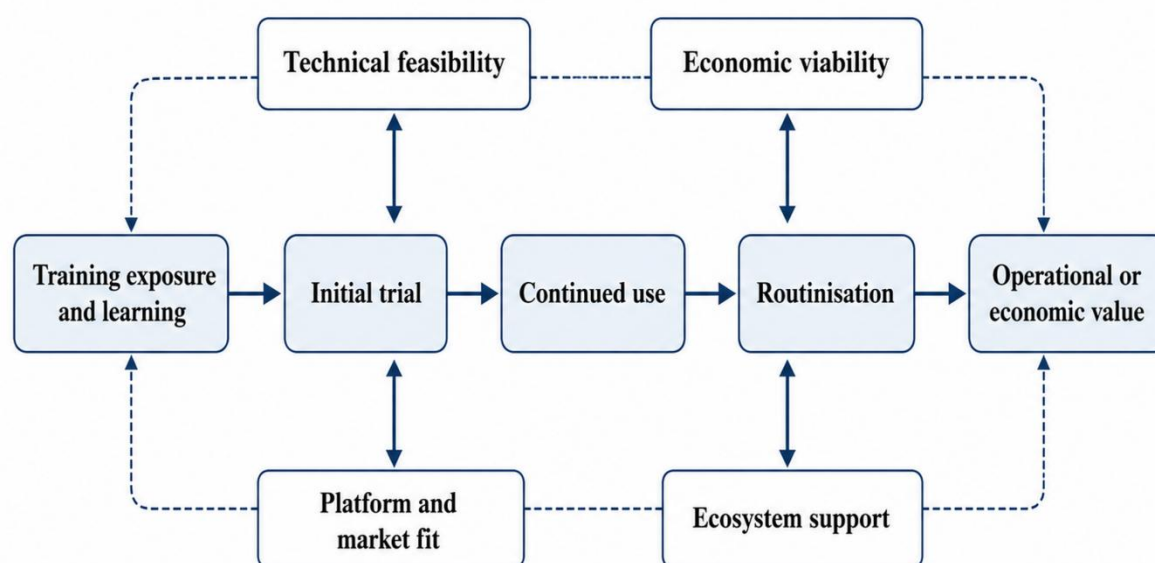


Figure 2. Proposed Conditional Conversion Framework for post-training digital application.

Note: The framework is literature-informed and proposed for future testing. The present survey measures only a broad indicator of post-training application and does not separately observe the stages or condition families shown.

3.5.1 Technical feasibility

Technical feasibility links an acquired capability to the material setting in which it can be exercised. Access to devices, reliable connectivity, usable data, and compatible systems may determine whether a participant can reproduce a procedure learned during training. For example, interpreting a monitoring dashboard has limited practical value when sensors are unavailable or data are incomplete. Once application begins, maintenance and interoperability may become more consequential because repeated use requires reliable integration with existing equipment and workflows. These distinctions are consistent with precision-agriculture

research on infrastructure, complexity, and compatibility (Barnes et al., 2019; Pierpaoli et al., 2013; Tey & Brindal, 2012), and suggest that technical conditions merit examination at both the trial and continued-use stages.

3.5.2 Economic viability

Economic viability concerns the relationship between the benefits of application and the resources needed to sustain it. A digital practice may be technically feasible yet difficult to maintain when subscription fees, maintenance, data entry, or specialist assistance impose recurring costs. Conversely, benefits may emerge only after sufficient records have accumulated or a complete production cycle has elapsed. Agricultural adoption research emphasises profitability, risk, resource availability, and the timing of returns (Feder et al., 1985; Foster & Rosenzweig, 2010; Lowenberg-DeBoer & Erickson, 2019). Within the proposed framework, anticipated affordability may be particularly relevant to initial trial, whereas experienced costs and benefits may shape subsequent continuation. Distinguishing these assessments would help clarify why willingness to experiment need not lead to sustained use.

3.5.3 Platform and market fit

For market- and service-oriented activities, the opportunity to apply digital skills is also embedded in relationships with customers, platforms, and other service providers. Operating an online account or producing digital content does not by itself secure transactions; application may depend on demand, trust, product standards, logistics, and platform rules. Research on agricultural platforms and digitalisation highlights the relevance of user perceptions, governance, and dependencies within these relationships (Cimino et al., 2024; Rotz et al., 2019). Platform and market fit therefore draws attention to the conditions connecting individual capability with a viable business process.

This perspective offers a possible interpretation of the higher reported application among production-oriented respondents in the fully adjusted model (OR = 2.743, $p = .001$). Where equipment and records are available, reading Internet of Things (IoT) sensor data or maintaining production records may provide an immediate occasion to apply a skill to a specific decision. Such tasks may have greater immediate instrumentality, in the sense that the link between the trained procedure and its practical use is readily identifiable. Customer engagement, platform positioning, and service coordination may instead require repeated adaptation and cooperation before application becomes visible. The distinction concerns task characteristics rather than an inherent advantage of production activities, which can also involve substantial complexity. Because task instrumentality and relational complexity were not measured, this interpretation remains provisional; differences in how respondents understood the broad outcome item also remain possible.

3.5.4 Ecosystem implementation support

The support needed to maintain application may extend beyond the trainer's capacity to answer course-related questions. Equipment problems may require a technician, interpreting digital outputs may require agronomic advice, and market participation may depend on logistics or cooperative arrangements. Digital advisory research describes this redistribution of knowledge and implementation responsibilities across public and private actors (Eastwood et al., 2019; Fielke et al., 2020; Ingram & Maye, 2020). Ecosystem implementation support thus concerns the accessibility and coordination of assistance across these actors, whereas PS captures only reported course-linked follow-up. Maintaining this distinction avoids treating the nonsignificant PS association as evidence about the effectiveness of the wider advisory system.

3.5.5 Implications for evaluation and intervention

Taken together, the four condition families suggest that training transfer may depend on combinations of capabilities and implementation opportunities. Relevant instruction and practice may support an initial attempt, while continued use may remain difficult if equipment is unreliable, recurring costs are high, or essential services are unavailable. The importance of these combinations is likely to vary across tasks and business settings. This makes progression through the application stages a more informative focus for evaluation than attendance or satisfaction alone, while leaving the proposed relationships open to empirical assessment.

Course-linked longitudinal observations could make these distinctions empirically tractable. Provider attendance records paired with independently scored practical assessments before and after training could distinguish exposure from learning. Time-stamped device or application logs could then identify a first completed task and subsequent use over a defined follow-up period. Finally, audited workflow records linked to input, labour, yield, or transaction records could indicate whether use became part of recurring decisions and whether operational value followed. These sources provide complementary evidence: repeated logins alone do not establish routine integration, and improved performance cannot be attributed to training without an appropriate baseline and comparison design.

For training providers, this approach would connect the evaluation of practical exercises, mentoring, and follow-up with the particular transition each component is intended to support. Comparative or phased interventions could examine whether assistance facilitates first use, prevents discontinuation, or improves integration into existing work. Recording delivery, uptake, and implementation costs alongside these outcomes would help distinguish an ineffective component from one that participants could not access or use.

The broader implication for extension provision is that capability development and implementation support need to be considered together. Their value also depends on accessibility, financial sustainability, and compatibility with users' control over data and decisions, concerns highlighted in responsible digitalisation research (Bronson & Knezevic, 2016; van der Burg et al., 2019). The framework therefore connects the study's transfer perspective with a focused agenda for examining sustained application, while preserving the boundary between the associations observed here and the mechanisms requiring further evidence.

3.6 Limitations and Future Research

This study has three principal limitations. First, the use of WeChat-linked convenience sampling restricts the generalisability of the findings. Although the sample included agricultural actors from diverse occupational and business backgrounds, it was not selected through probability-based procedures and may overrepresent individuals who are more digitally connected or more closely involved in agricultural training networks. Selection may raise the sample's baseline digital literacy relative to less-connected actors and narrow variation in digital readiness, potentially obscuring some associations. However, neither the direction nor magnitude of selection bias can be determined without pre-training measures and information on nonparticipants. The findings should therefore be interpreted as exploratory evidence from the surveyed respondents rather than as population-level estimates for Chinese agricultural actors. Future studies could strengthen external validity through probability-based stratified or multi-stage sampling across regions, business types, and occupational groups, with offline recruitment to include actors with limited digital access.

Second, the measurement design limits the precision with which training transfer can be evaluated. Post-training digital application, training-content relevance, and course-linked support were measured using broad retrospective single-item indicators, while the inverse scenario/practice-barrier index was constructed from two reported barriers. In addition,

respondents who attended multiple courses during the preceding two years were not asked to evaluate a clearly specified reference course. These features may have introduced measurement error and weakened the alignment between the predictors and the outcome. The broad application item may also have been interpreted differently by production-, market-, and service-oriented respondents. Future research should employ validated multi-item measures, identify a specific training event, and distinguish learning, initial trial, continued use, routinisation, and operational value through task- and sector-specific indicators.

Third, the cross-sectional and associational design does not support causal inference or identify the mechanisms underlying the nonsignificant focal estimates. The analysis did not directly measure several conditions that may influence post-training application, including prior digital capability, access to technology, economic feasibility, platform and market fit, provider quality, and broader implementation support. Accordingly, the proposed Conditional Conversion Framework should be regarded as a literature-informed agenda for empirical testing rather than as an explanation established by the present results. Future research could use prospective longitudinal, experimental, or mixed-method designs to examine how training characteristics interact with technical, economic, organisational, and institutional conditions at different stages of application. Course-linked observations, objective usage records, performance indicators, and interviews would provide stronger evidence regarding when and under what conditions digital-skills training becomes embedded in agricultural practice.

4. Conclusion

Using questionnaire data from 156 Chinese agricultural actors, this study examined whether perceived training-content relevance, fewer scenario and hands-on-practice barriers, and stronger course-linked post-training support were associated with higher reported post-training digital application. The ordered-logit analysis did not detect the three hypothesised direct associations, and the substantive decisions remained unchanged under categorical predictor coding and expanded adjustment. Production-oriented respondents reported higher levels of application than market- or service-oriented respondents, although this secondary association may reflect differences in application opportunity, activity context, or interpretation of the broad outcome measure. This broad self-reported outcome does not establish technology-specific smart-farming adoption, sustained use, or performance.

The study contributes by distinguishing training participation and learning from initial trial, continued use, routinisation, and operational value. This distinction shifts evaluation away from the assumption that course attendance or favourable training perceptions necessarily translate into sustained practice. The proposed Conditional Conversion Framework provides a heuristic for future research, positing that progression across application stages may depend on configurations of technical feasibility, economic viability, platform and market fit, and ecosystem implementation support. These conditions may operate differently across technologies, business activities, and stages of use and should therefore be measured directly in future research.

For training providers and extension organisations, the principal implication is to evaluate the application pathway rather than the course alone. Programme assessment should combine evidence of learning with task-specific measures of trial, repeated use, workflow integration, and operational outcomes. Training components such as practical exercises, follow-up assistance, demonstration sites, technical services, and advisory support should be evaluated as testable interventions within clearly defined implementation contexts. Course-linked longitudinal data, objective usage or performance records, and more precise measures of the surrounding application environment will be necessary to determine when digital-skills training becomes embedded in agricultural practice.

Data Availability

The de-identified analytical dataset, analysis code, and coding notes are available from the corresponding author at sylviaapple1986@gmail.com upon reasonable request for non-commercial academic verification, subject to participant consent and applicable institutional requirements. Requests should specify the intended use and materials required. IP-address metadata will not be shared.

Author Contributions

Fan Mo: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing, Reviewing, and Editing.

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Conflicts of Interest

The author declares no conflict of interest.

Ethics Statement

Participation was voluntary; all respondents were adults, and questionnaire data were analysed without direct personal identifiers. Guangdong AIB Polytechnic granted an exemption from institutional ethics review for the data collection in this study.

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Appendix A

Table A1. Approximate provincial-level distribution of analytical records derived from platform IP metadata.

IP-derived provincial-level location	N	Percentage (%)
Jiangsu	48	30.8
Zhejiang	39	25.0
Guangdong	14	9.0
Fujian	13	8.3
Shandong	9	5.8
Anhui	5	3.2
Hainan	4	2.6
Hebei	4	2.6
Hubei	3	1.9
Jiangxi	3	1.9
Qinghai	2	1.3
Guangxi	2	1.3
Henan	2	1.3
Sichuan	2	1.3
Shanghai	2	1.3
Inner Mongolia	1	0.6
Liaoning	1	0.6
Guizhou	1	0.6
Chongqing	1	0.6
Total	156	100.0

Note: IP-derived location is approximate and was not treated as a verified residence, farm location, or sampling stratum. It is reported solely to describe the geographic dispersion of the final online records.