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Development of a Hybrid Data-Driven Decision Framework for the Adoption of Smart Farming

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Abstract: Smart farming brings together digital tools and data-enabled services—such as mobile agricultural applications, weather information, sensors, Internet of Things (IoT) devices, remote sensing, precision input technologies, and digital advisory platforms—to support farm-management decisions. However, technology adoption is not determined by technical availability alone. Farmers may weigh expected usefulness against affordability, digital literacy, connectivity, trust in providers, perceived risk, access to training, and the availability of repair and after-sales support. This paper presents a pilot-study design intended to refine a questionnaire and inform the development of a hybrid data-driven decision framework for matching smart-farming options to farmers' needs, resources, and operating conditions. To demonstrate the planned analysis, a practice dataset of 50 simulated records was analysed using respondent-profile frequencies, construct-level descriptive statistics, and Cronbach's alpha for eight three-item constructs. In this illustrative dataset, 36 of 50 records were coded as using at least one smart-farming tool, perceived usefulness had the highest mean score (M = 3.53, SD = 0.90), while training and extension support had the lowest (M = 2.53, SD = 0.92). Illustrative alpha coefficients ranged from 0.797 to 0.885 across the eight constructs. These values demonstrate reporting procedures only and do not estimate reliability among actual farmers. The paper details the research problem, conceptual grounding, objectives, questions, proposed hypotheses, methodology, illustrative results, and a transparent multi-criteria decision framework. The next stage is genuine pilot fieldwork, instrument refinement, and subsequent validation using an appropriately designed main study.

Keywords: smart farming; technology adoption; pilot study; digital literacy; affordability; Cronbach's alpha; decision-support framework; multi-criteria decision analysis; agriculture.

1. Introduction

Agricultural decisions increasingly involve information about weather, soil and crop conditions, irrigation, nutrient application, pests, input prices, market access, and production risk. Digital technologies can help collect, organise, interpret, and communicate such information. The term smart farming is used here as an umbrella for data-enabled practices and tools that support agricultural planning and operations, including mobile advisory services, digital marketplaces, weather applications, remote sensing, sensors, connected equipment, and precision agriculture solutions. The relevance of any specific tool depends on the farm context, crop system, scale of operation, local infrastructure, and the user's capacity to operate and maintain it.

The availability of a technology does not guarantee adoption. A farmer may perceive a tool as useful but consider its initial price or recurring subscription unaffordable. Another farmer may be able to pay for it but lack reliable connectivity, confidence in interpreting digital information, or access to local support when the system fails. Concerns about uncertain returns, maintenance costs, privacy, data ownership, and the reliability of advice may also shape purchase and continued-use decisions. These factors suggest that technology selection should consider both technical feasibility and farmer behaviour rather than relying on a single adoption indicator.

Technology acceptance research provides a basis for considering perceived usefulness and user beliefs in technology decisions (Davis, 1989). Diffusion of Innovations emphasises how innovations are communicated and

adopted within social systems, including the importance of perceived characteristics and contextual conditions (Rogers, 2003). The Unified Theory of Acceptance and Use of Technology integrates several determinants of technology acceptance and use (Venkatesh et al., 2003). In agricultural settings, these perspectives need to be interpreted alongside practical constraints such as financing, connectivity, service access, and extension support. FAO's work on agricultural automation also underscores the need to consider the broader conditions under which technologies can contribute to agrifood-system transformation (FAO, 2022).

The present study therefore has two linked purposes. First, it proposes a pilot survey to test whether the questionnaire, construct definitions, response options, and data-management procedures are suitable for a larger study. Second, it specifies how the resulting evidence could inform a hybrid data-driven decision framework. "Hybrid" refers to the planned combination of structured data, behavioural and contextual assessment, transparent decision rules, multi-criteria ranking, and human review. The framework is proposed at this stage; its effectiveness cannot be claimed until it is implemented and evaluated with genuine data and stakeholder feedback.

2. Problem Statement and Rationale

Smart-farming adoption involves multiple interacting conditions, yet a technology recommendation can be incomplete if it considers only expected performance or availability. A technically capable tool may be inappropriate where connectivity is unreliable, where the farmer cannot access training, or where the total cost of ownership is incompatible with available resources. Conversely, an inexpensive tool may provide limited value if it does not address the farmer's priority problem. A decision process that makes these trade-offs visible could help farmers, extension personnel, technology providers, and institutions compare feasible options more systematically.

A methodological challenge precedes the development of such a framework: the study requires a clear, usable instrument for measuring relevant constructs and documenting farmers' actual technology use, purchasing behaviour, and constraints. Without pilot testing, items may be ambiguous, constructs may overlap, response categories may not fit local circumstances, and data-entry procedures may introduce errors. The pilot must therefore be treated as an instrument and process-development stage, not as a substitute for a sufficiently powered and appropriately sampled main study.

3. Aim, Objectives and Research Questions

3.1 Aim

To develop a hybrid data-driven decision framework that supports the adoption of smart-farming technologies by matching technology options to farmers' needs, resources, capabilities, and operating circumstances.

3.2 Research objectives

1. Examine stakeholders' perceptions regarding the current status of smart-farming adoption.
2. Assess the extent of smart-farming implementation among participating farmers.
3. Identify technologies, methods, tools, and platforms commonly used by adopters.
4. Analyse farmers' buying behaviour and purchase intentions regarding smart-farming technologies.
5. Identify constraints and challenges affecting adoption and implementation.
6. Develop a hybrid data-driven techno-behavioural decision framework that matches technology options to farmers' needs, resources, and circumstances.

3.3 Research questions

1. How do farmers perceive the usefulness and practical relevance of smart-farming technologies?

2. What is the reported extent of smart-farming implementation among participating farmers?
3. Which technologies, methods, tools, and platforms are used, and for what purposes?
4. How do farmers evaluate cost, financing, expected benefits, trust, and risk when considering a purchase?
5. Which behavioural, financial, infrastructural, and institutional constraints are reported?
6. How can farmer-readiness information and technology attributes be combined into a transparent, explainable decision framework?

4. Conceptual Background and Study Constructs

The study organises the proposed questionnaire around eight constructs. They are working measurement domains, not yet validated scales. Each construct is represented by three Likert-style items in the practice workbook. The final wording, translations, scoring, and applicability should be reviewed with subject experts and target respondents before field deployment.

Construct	Working definition	Mmeasurement focus
Perceived usefulness	Belief that smart-farming tools can improve farm decisions or operations.	Timeliness and relevance of information; resource management; perceived decision quality.
Digital literacy	Perceived ability to access, operate, and interpret digital tools and information.	Using applications; interpreting information; learning or troubleshooting tools.
Affordability	Perceived financial feasibility of acquiring and maintaining a technology.	Initial cost; recurring fees; access to finance or subsidies; expected value.
Trust in providers	Confidence in technology suppliers, advisory sources, and service reliability.	Credibility; accuracy; transparency; availability of assistance.
Infrastructure adequacy	Availability of enabling resources needed for practical use.	Connectivity; electricity; suitable devices; repair and service access.
Training and extension support	Access to instruction and continuing guidance.	Hands-on training; local-language advice; demonstrations; follow-up assistance.
Perceived risk	Perceived possibility of financial, operational, performance, or privacy loss.	Uncertain benefits; failure; maintenance; privacy and data concerns.
Adoption intention	Stated willingness or plan to adopt or continue using a suitable technology.	Intention within a defined period; purchase consideration; continued-use expectation.

These domains reflect a combined behavioural and practical perspective. Perceived usefulness and intention relate to technology-acceptance theory, while the remaining constructs capture financial feasibility, trust, infrastructure,

support, and risk that may affect whether an intention can be translated into use. The constructs should be examined for conceptual overlap and should not be assumed to represent eight independent causal factors.

5. Proposed Hypotheses for the Main Study

The following hypotheses are proposed for testing with genuine main-study data. They are not tested by the simulated pilot dataset in this paper. The exact dependent variable and statistical model should be finalised before the main analysis, with adoption intention kept distinct from observed adoption status.

Code	Proposed relationship	Potential analysis
H01	Perceived usefulness is positively associated with adoption intention.	Spearman correlation; regression if assumptions and coding are appropriate.
H02	Digital literacy is positively associated with adoption intention or adoption status.	Spearman correlation for ordinal scores; logistic regression for binary status where suitable.
H03	Perceived affordability is positively associated with purchase intention or adoption.	Correlation or suitable regression; distinguish intention from actual purchase.
H04	Trust in providers is positively associated with adoption intention.	Correlation or regression, with construct overlap checked.
H05	Infrastructure adequacy is positively associated with implementation extent.	Correlation or ordinal regression after defining the implementation measure.
H06	Training and extension support are positively associated with continued-use intention.	Correlation or regression; specify how non-users are treated.
H07	Perceived risk is negatively associated with purchase intention.	Correlation or suitable regression, with risk items coded consistently.
H08	Adoption status differs across selected farmer and farm characteristics.	Chi-square or an appropriate regression/model, subject to expected cell counts and variable types.

6. Research Methodology

6.1 Research design

The proposed study uses a staged, survey-based design. The pilot stage assesses questionnaire clarity, feasibility, data quality, scoring, and preliminary reliability. It is followed by instrument revision and a larger empirical study to examine adoption patterns and relationships and to provide evidence for the decision framework. A cross-sectional survey can identify associations but, by itself, cannot establish causal effects or demonstrate that a framework improves farm outcomes.

6.2 Pilot sample and status of the dataset

The report supplied for this paper contains 50 simulated records. These records are used solely to demonstrate the analytical workflow. They do not represent recruited participants, completed questionnaires, or a field sample.

Consequently, the frequencies and scores below cannot be generalised to any farmer population and cannot be used to claim the prevalence of adoption or actual construct reliability.

6.3 Questionnaire structure

The practice instrument contains respondent-profile variables, an adoption-status indicator, a main-constraint category, a preferred-support category, and three Likert-style items for each of eight constructs. The construct items use a five-point response scale. Before actual use, the questionnaire should define the response anchors, reference period, technology examples, and the meaning of "adoption." It should distinguish current use, past use, purchase, intention to purchase, and continued use. A "not applicable" option may be needed for respondents who have never used a technology.

6.4 Sampling and field procedures for the real pilot

The final study setting, recruitment sites, sampling frame, eligibility criteria, and sampling procedure remain to be specified. The real pilot should recruit participants who reflect the intended target group and relevant variation in farm size, crop type, age, education, technology exposure, and access to infrastructure. The study should record the number approached, eligible, consenting, completing, and excluded, along with reasons for exclusion. A pilot sample of 50 may help reveal questionnaire and operational issues but should not automatically be treated as adequate for population estimates, factor analysis, or stable subgroup comparisons.

6.5 Data quality and scoring

For genuine responses, the data-management process should include range checks, duplicate checks, missing-value summaries, review of unusual response patterns, and documentation of any exclusions. Negatively worded items must be reverse-coded before composite scores are calculated. A construct score may be computed as the mean of its three items only when the scoring rule is justified and missing-item handling is specified in advance. The analysis log should retain the original data, a cleaned version, a codebook, and reproducible syntax or scripts.

6.6 Reliability analysis

Cronbach's alpha is proposed as one preliminary indicator of internal consistency for each multi-item construct. Alpha should be interpreted alongside item wording, corrected item-total correlations, alpha-if-item-deleted diagnostics, dimensionality, and the construct's conceptual coverage. A coefficient near .70 is sometimes used as a rough screening reference, not a universal pass/fail rule. High alpha does not prove validity or unidimensionality; low alpha does not automatically justify deleting an item. The pilot's purpose is to diagnose and improve the instrument, not to manipulate responses to obtain a preferred coefficient (Tavakol & Dennick, 2011).

6.7 Planned main-study analysis

The main analysis should begin with descriptive summaries and data-quality reporting. Hypothesis tests should then be chosen according to the operational definitions and distribution of each variable. Spearman's rank correlation may be appropriate for monotonic relationships involving ordinal or non-normally distributed scores. Logistic regression may be considered for a clearly defined binary adoption outcome when the sample size, coding, and model assumptions support it. Chi-square tests may be appropriate for categorical differences if expected cell counts are adequate. Report effect sizes, confidence intervals, exact p-values where available, and model diagnostics. Avoid causal language unless supported by a suitable design.

7. Results from the Simulated Dataset

This section reproduces the structure of the supplied pilot report. Every value below is generated from simulated data. It is included to demonstrate how results may be presented after genuine data collection; it is not evidence about actual farmers.

7.1 Record profile

Variable	Category	Frequency (n=50)	Percentage
Age group	18–30	4	8%
Age group	31–40	8	16%
Age group	41–50	11	22%
Age group	51–60	19	38%
Age group	Above 60	8	16%
Adoption status	Using at least one tool	36	72%
Adoption status	Not yet adopted	14	28%

In the simulated file, the largest age category is 51–60 years (19 records, 38%). Thirty-six records are coded as using at least one tool and 14 as not yet adopted. These proportions are artefacts of the generated practice data; they must not be interpreted as a real adoption rate or as evidence that adoption is higher in any age group.

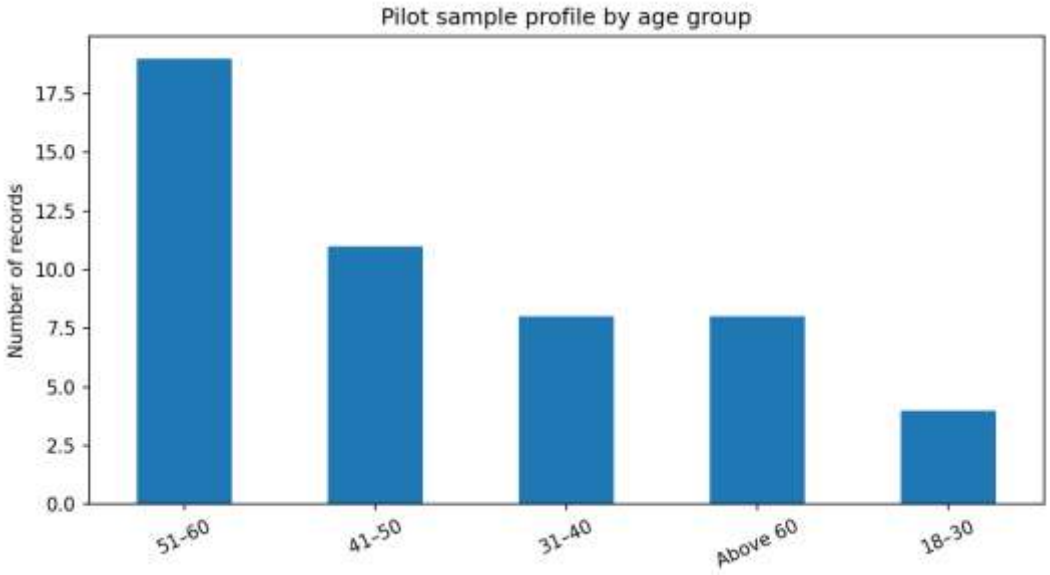


Figure 1. Illustrative age-group distribution in the simulated dataset.

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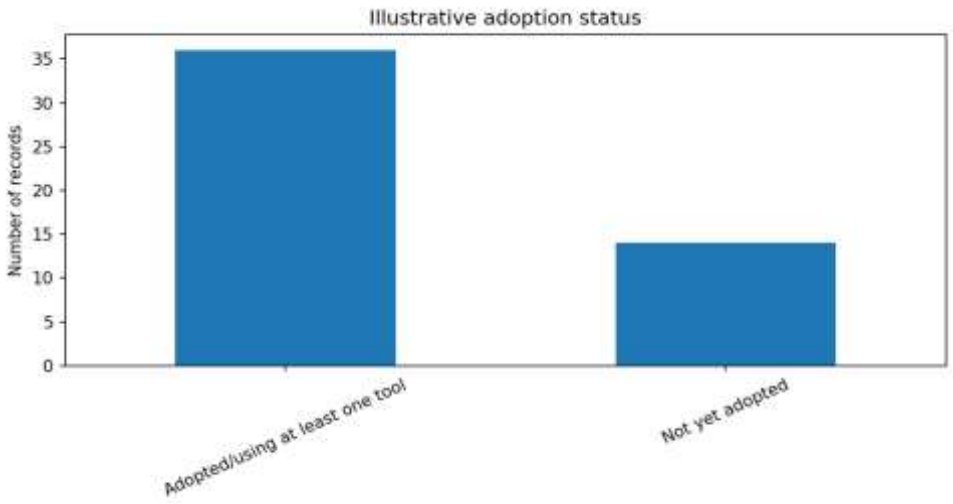


Figure 2. Illustrative adoption-status distribution in the simulated dataset.

7.2 Constraints and preferred support

Main constraint	Frequency	Percentage
Lack of training	11	22%
High cost	9	18%
Limited digital skills	9	18%
Uncertain benefits	8	16%
Poor connectivity	8	16%
Service/maintenance	5	10%

Preferred support	Frequency	Percentage
Demonstration farms	16	32%
Subsidy/finance	13	26%
Hands-on training	7	14%
Local-language advice	6	12%
Reliable internet	4	8%
After-sales service	4	8%

In the simulated data, lack of training is the most frequent constraint category (11/50), followed by high cost and limited digital skills (9/50 each). Demonstration farms and subsidy/finance are the two most frequently selected support options. This pattern demonstrates how a survey can translate broad concerns into actionable categories; it does not establish the priority of these issues among real respondents. The actual questionnaire should allow

participants to select multiple constraints if appropriate, or clearly state that they must choose one primary constraint.

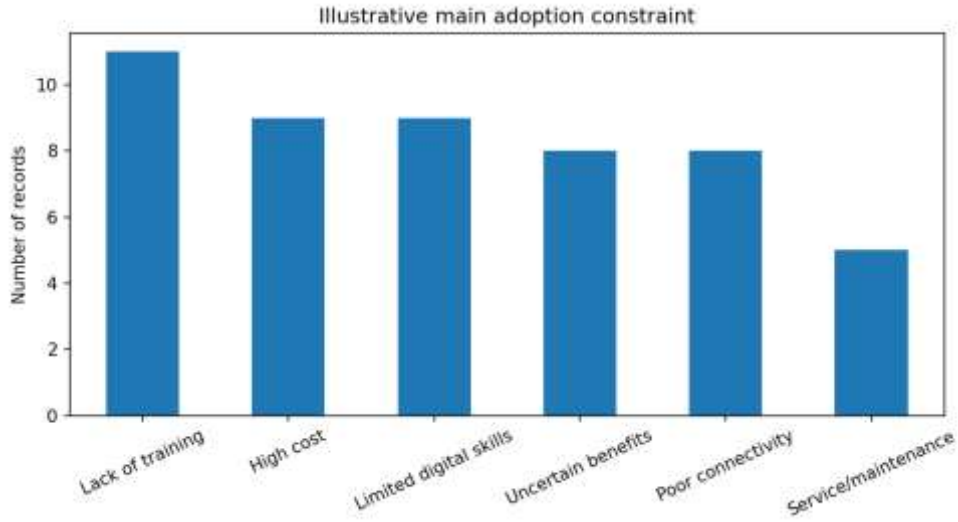


Figure 3. Illustrative main-constraint frequencies.

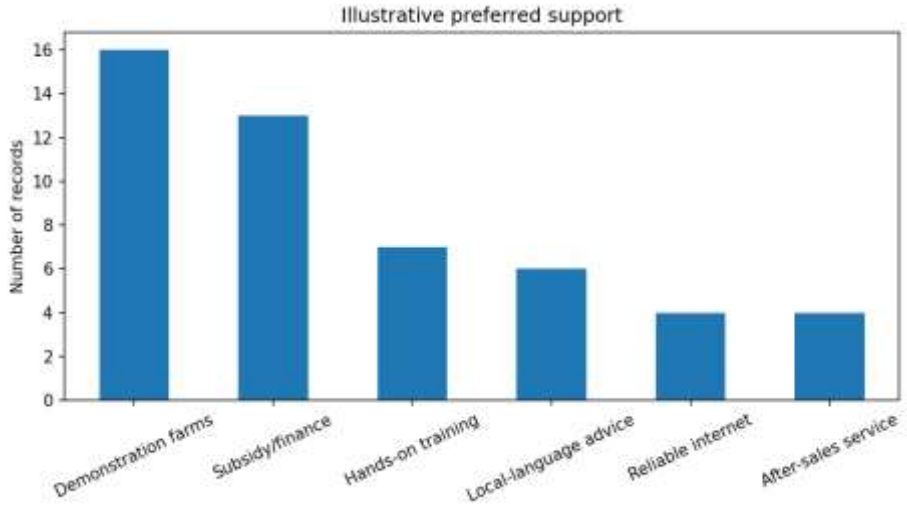


Figure 4. Illustrative preferred-support frequencies.

7.3 Construct descriptive statistics

Construct	N	Mean	SD	Minimum	Maximum
Perceived usefulness	50	3.53	0.90	2.00	5.00
Digital literacy	50	3.03	0.99	1.00	5.00
Affordability	50	3.05	0.87	1.33	5.00
Trust in providers	50	3.11	0.94	1.33	5.00

Infrastructure adequacy	50	2.75	0.78	1.00	4.33
Training/extension support	50	2.53	0.92	1.00	4.67
Perceived risk	50	3.18	0.87	1.00	5.00
Adoption intention	50	3.04	1.01	1.00	5.00

The simulated construct means range from 2.53 for training and extension support to 3.53 for perceived usefulness among the values reported in the pilot summary. The usefulness mean is above the midpoint of the five-point scale, while training/extension support and infrastructure adequacy are below the midpoint. If a comparable pattern were observed in actual fieldwork, it would warrant closer investigation of the availability, relevance, and accessibility of training and infrastructure. In this paper, however, such an interpretation is strictly hypothetical because the values are simulated. The adoption-intention score in the simulated workbook has a mean of 3.04 (SD = 1.01), with values from 1.00 to 5.00. These figures are also illustrative only and are not inferred from actual field responses.

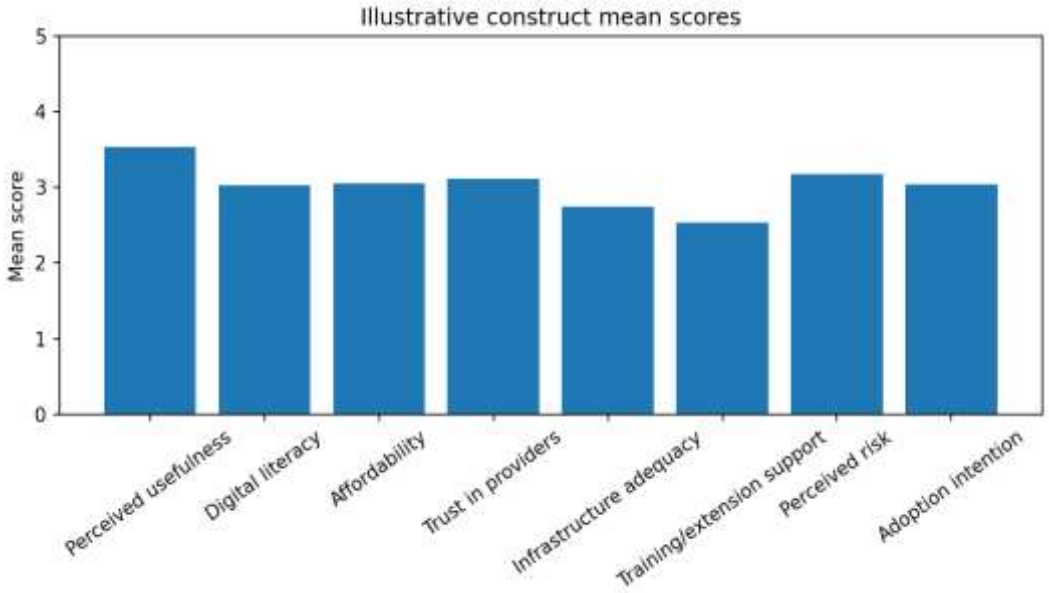


Figure 5. Mean scores for the reported constructs.

7.4 Illustrative internal consistency estimates

Construct	Items	N	Cronbach's alpha (simulated)
Perceived usefulness	PU1–PU3	50	0.885
Digital literacy	DL1–DL3	50	0.838
Affordability	AF1–AF3	50	0.821
Trust in providers	TR1–TR3	50	0.836
Infrastructure adequacy	IA1–IA3	50	0.797

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Training/extension support	TE1–TE3	50	0.873
Perceived risk	PR1–PR3	50	0.819
Adoption intention	AI1–AI3	50	0.826

The illustrative coefficients range from 0.797 to 0.885. In this generated example, all eight values exceed the commonly cited .70 screening reference. This should not be presented as evidence that the proposed scales are reliable in a farmer population: the responses were generated computationally, and real-world item behaviour may differ substantially. For actual pilot data, the researcher should report corrected item-total correlations and alpha-if-item-deleted values, examine whether items cover the intended construct, and document all revisions.

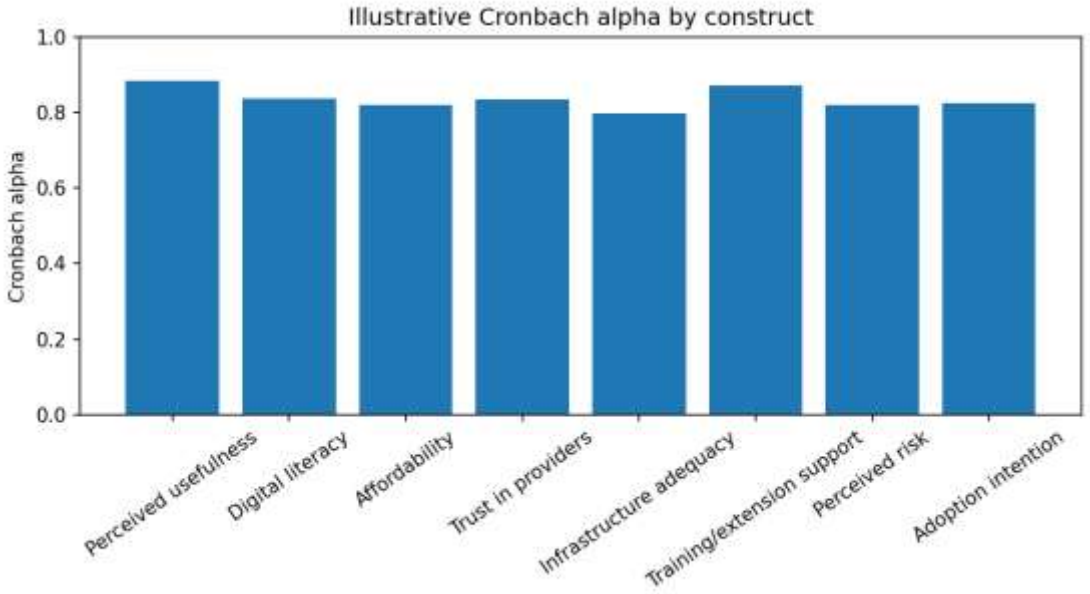


Figure 6. Cronbach's alpha coefficients for multi-item constructs.

7.5 What the pilot analysis can and cannot establish

Can demonstrate methodologically	Cannot establish from simulated data
How to format frequency tables and charts.	Actual farmer demographics or adoption prevalence.
How to calculate construct means and standard deviations.	Empirical levels of usefulness, literacy, affordability, trust, infrastructure, support, or risk.
How to structure construct-wise reliability reporting.	Actual reliability or validity of the questionnaire.
How to organise a data-cleaning and analysis workflow.	Statistically supported relationships or hypothesis acceptance/rejection.
How survey outputs might inform a decision framework.	That the proposed framework improves decisions, adoption, productivity, or farm outcomes.

8. Discussion

The central methodological lesson from this pilot exercise is that a useful smart-farming adoption study should measure more than whether a respondent currently uses a tool. Adoption status alone does not reveal whether the technology is suitable, affordable, trusted, well supported, or used effectively. A structured questionnaire can help distinguish current use from intention, purchase behaviour, implementation extent, and continued use. It can also capture barriers that may be addressed through training, financing, infrastructure, or service arrangements.

The illustrative tables show how the study could make the analysis actionable. Constraint categories can be linked to intervention options: training needs may suggest practical demonstrations and follow-up assistance; affordability concerns may prompt transparent total-cost estimates and examination of financing options; connectivity limitations may require offline-capable tools or infrastructure solutions; service concerns may make provider support and repair access important selection criteria. These are design implications, not conclusions about the frequency or severity of actual constraints.

The construct-level analysis also highlights the need to keep measurement and decision-making separate. A reliability coefficient is a property of observed item responses in a particular sample and context; it is not a direct measure of whether a technology is suitable for a particular farm. Similarly, an average construct score should not be treated as a definitive recommendation. A decision framework must combine the farmer's priorities with observable technology attributes and feasibility constraints, and it should explain why an option is ranked highly or excluded.

The proposed framework should therefore be developed iteratively. Early stakeholder consultations can clarify criteria and acceptable trade-offs. A transparent scoring method can then compare eligible options, with weights documented rather than selected to produce a desired ranking. Sensitivity analysis should test whether rankings change when weights or input scores vary. Finally, usability testing should establish whether farmers and extension workers understand the recommendations and can use them in practice.

9. Proposed Hybrid Data-Driven Decision Framework

The framework is conceptual and requires separate development and validation. Its purpose is to combine structured data with transparent rules and human judgement so that recommendations reflect both technology characteristics and farmer circumstances.

Stage	Function	Illustrative inputs / outputs
1. Farmer and farm profile	Establish the decision context.	Farm size, crop, production priorities, resources, digital experience, risk preferences.
2. Needs assessment	Identify the problem the farmer wants to solve.	Irrigation efficiency, weather risk, crop monitoring, input management, market information.
3. Readiness assessment	Assess enablers and constraints.	Affordability, literacy, connectivity, electricity, trust, training, maintenance access.
4. Technology feasibility screening	Remove options that do not meet essential requirements.	Minimum connectivity, compatible devices, technical fit, service availability, total cost.

5. Multi-criteria ranking	Compare feasible options against documented criteria.	Normalised criteria scores, weights, ranked shortlist, sensitivity results.
6. Explanation and human review	Communicate recommendation and trade-offs.	Reasons for ranking, cost assumptions, support requirements, limitations, alternatives.
7. Feedback and updating	Improve profiles and recommendations over time.	Usage, satisfaction, service performance, farmer feedback, observed outcomes.

9.1 Candidate scoring structure

A transparent weighted score for technology option i may be represented as:

$$\textbf{Score}(i) = \Sigma_j \, w_j \times s_{ij}$$

Here, w_j represents the weight assigned to criterion j and s_{ij} is the score of option i on that criterion. Where weights are normalised, their sum should equal 1. Before ranking, criteria should be defined clearly, scoring scales aligned, and cost or risk criteria oriented consistently so that the meaning of a higher score is unambiguous. Weights may be elicited from farmers and domain experts or estimated through a justified procedure. They should not be chosen to guarantee a preferred outcome. Sensitivity analysis should test alternative plausible weights and uncertain technology ratings.

9.2 Human oversight and explainability

The framework should not operate as an unexplained automated recommendation engine. It should show why an option is recommended, what assumptions are used, which constraints could prevent successful use, and what further information is needed. Farmers should be able to challenge or override a recommendation. Data minimisation, informed consent, secure storage, clear access rules, and transparency about data use should be integrated into the design. The framework should also avoid assuming that digital technologies are universally beneficial; suitability depends on the problem being addressed and on local conditions.

10. Ethical Considerations and Data Governance

The real study should be conducted only after the required institutional permissions and ethics procedures have been determined and completed. Participation should be voluntary and based on informed consent. Participants should receive an understandable explanation of the study purpose, the information being collected, how the data will be used, and any applicable withdrawal arrangements. The questionnaire should collect only information needed to answer the research questions. Direct identifiers should be separated from analytical data where feasible, files should be securely stored, access should be limited, and results should be reported in aggregate. The paper must describe only approvals, consent procedures, and fieldwork that actually occurred.

11. Limitations

The most important limitation is that the current numerical analysis uses simulated records. It cannot establish actual perceptions, adoption prevalence, purchasing behaviour, constraint priorities, construct reliability, hypothesis relationships, or population-level conclusions. The dataset was generated for demonstration and may not reproduce the response patterns, missingness, heterogeneity, or measurement difficulties found in fieldwork.

The final study geography, recruitment plan, sampling frame, target population, questionnaire wording, translations, ethics arrangements, and fieldwork dates also remain to be confirmed. A pilot sample is intended

primarily to improve the instrument and procedures and may not support factor analysis or stable subgroup comparisons. The proposed decision framework is conceptual; its usefulness, fairness, explainability, ranking stability, and practical effects remain to be evaluated. Cross-sectional survey evidence, if used, would support association rather than causal claims.

12. Recommendations and Next Steps

1. Confirm the study setting, target population, eligibility criteria, recruitment sites, and sampling procedure.
2. Obtain the necessary institutional and ethics approvals before recruiting participants.
3. Review the questionnaire with subject experts and a small group of target respondents; check wording, translation, response burden, and technology examples.
4. Collect genuine pilot responses and document approached, eligible, consenting, completed, and excluded cases.
5. Screen the data for missingness, duplicates, out-of-range values, and coding inconsistencies; preserve an audit trail.
6. Calculate construct scores and reliability diagnostics from actual responses, including corrected item-total correlations and alpha-if-item-deleted values.
7. Revise the instrument based on documented evidence rather than altering responses to obtain desired statistics.
8. Use the pilot to refine the main-study analysis plan; predefine outcomes, predictors, coding, and statistical tests.
9. Develop the decision framework with farmer, extension, and technology-provider input; document criteria and weights.
10. Validate framework recommendations through usability testing, expert review, sensitivity analysis, and an evaluation plan using real-world cases.

13. Conclusion

This paper presents a detailed pilot-study structure for research on smart-farming adoption and the development of a hybrid data-driven decision framework. It brings together eight proposed constructs, a questionnaire-development workflow, reliability diagnostics, a planned hypothesis-testing strategy, and a transparent multi-criteria recommendation process. The simulated 50-record analysis demonstrates how frequencies, descriptive statistics, charts, and Cronbach's alpha can be reported. It does not provide empirical evidence about farmers. The immediate research priority is to conduct genuine, ethically appropriate pilot fieldwork, refine the instrument based on observed evidence, and then undertake the main study and framework validation. Maintaining this distinction between illustrative analysis and empirical results is essential to the credibility and reproducibility of the research.

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