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Research Article

Trust Conditions and Regulatory Protection in AI Based Agricultural Information in Bangladesh

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ABSTRACT

AI-supported agricultural information may provide useful guidance while raising concerns about local suitability, accountability and oversight. This study examines stated trust conditions and perceptions of regulatory protection in a Bangladesh survey. The 385 adult, AI-aware records comprise law students, graduates, legal professionals and other respondents; 60 report a location classified as upazila or rural. The file does not identify farmers or establish that respondents use agricultural AI, so findings concern a mixed sample rather than representative rural users. The analysis retains separate questionnaire items and compares paired endorsement of statements on source/provider clarity, regulatory oversight and accountability. It also explores correlations between AI awareness items and two trust-related statements. Of 385 respondents, 310 (80.5%) agreed that clear sources and a responsible provider would increase trust, 255 (66.2%) agreed that regulatory oversight can increase confidence, and 317 (82.3%) agreed that strong accountability increases willingness to use agricultural AI. Source/provider clarity exceeded oversight endorsement by 14.3 percentage points; 210 respondents endorsed both statements. These are differently worded hypothetical propositions, so their contrast is not a ranking of interventions or evidence of causal effects. Associations between awareness and trust conditions were small and do not establish that training changes reliance. The study contributes an item-level distinction between provider transparency, institutional oversight, local adaptation and accountability, and proposes a future design that evaluates specific advisory systems with actual agricultural users.

Keywords: agricultural artificial intelligence; regulatory protection; trust; provider transparency; accountability; Bangladesh

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1. Introduction

Agricultural information can influence crop selection, irrigation, pest management, marketing and other decisions with practical costs. Digital systems may make guidance easier to access and can support extension services, but their recommendations must be judged against local growing conditions, the quality and provenance of the information used and the availability of qualified human advice. A fluent answer is not evidence that a recommendation is accurate. A recent review of AI and machine learning in agriculture identifies interconnected concerns about data governance, reliability, digital access and explainability.[1]

Bangladesh is an important context for studying digital agricultural services because access, infrastructure, language and trust may vary across communities and decision settings. Existing digital-agriculture scholarship also highlights unequal control of data and the need to involve end users in design.[2] The present records, however, do not identify respondents as farmers or confirm that they have used agricultural AI. They provide evidence of the recorded mixed sample's stated perceptions, not national estimates for the rural agricultural population.

Trust in an AI system is often discussed as though it were a single attitude. A person may instead distinguish knowing the responsible provider, having a route to report harm, believing that public oversight is effective, and receiving locally appropriate advice. Each condition can affect reliance differently. Regulatory protection in particular should not be inferred from confidence in an individual provider. Conversely, endorsement of oversight does not establish that an effective institution exists or that a particular service complies with law.

Earlier research on digital farming highlights that the service provider, the person receiving advice and the institution responsible for a remedy can be different actors. An apparently reliable recommendation can therefore raise questions at several stages: who supplied the evidence, who checked its local suitability and who will respond if the advice is harmful.[3] The article focuses on differences among these stated conditions. Its distinctive analytical choice is to compare how the same individuals respond to specific propositions on source and provider clarity, oversight, accountability and local adaptation. These questions have different wording and are not forced-choice alternatives. Their comparison can reveal different response distributions, but cannot rank their causal effects on trust. The work uses Trust Theory and the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) as complementary perspectives rather than asserting that the survey validates either model.[4]

The objective is to describe and compare reported trust conditions and governance preferences for AI-supported agricultural information. Four questions guide the analysis: How often are clarity, oversight, accountability and reporting endorsed? How do responses to source/provider clarity and regulatory oversight coexist within respondents? How are selected

[1] Richa Bhattarai and others, 'Scale, Trust, and the Digital Divide: A Systematic Review of AI and ML for Agricultural Applications' (2026) 9 Frontiers in Artificial Intelligence 1798896.

[2] Laurens Klerkx, Emma Jakku and Pierre Labarthe, 'A Review of Social Science on Digital Agriculture, Smart Farming and Agriculture 4.0: New Contributions and a Future Research Agenda' (2019) 90–91 NJAS: Wageningen Journal of Life Sciences 100315; Callum Eastwood and others, 'Managing Socio-Ethical Challenges in the Development of Smart Farming: From a Fragmented to a Comprehensive Approach for Responsible Research and Innovation' (2019) 32 Journal of Agricultural and Environmental Ethics 741.

[3] Klerkx, Jakku and Labarthe (n 2); Isabelle M Carbonell, 'The Ethics of Big Data in Big Agriculture' (2016) 5(1) Internet Policy Review, DOI: 10.14763/2016.1.405.

[4] Viswanath Venkatesh, James YL Thong and Xin Xu, 'Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology' (2012) 36 MIS Quarterly 157; Roger C Mayer, James H Davis and F David Schoorman, 'An Integrative Model of Organizational Trust' (1995) 20 Academy of Management Review 709.

self-reported AI-awareness items associated with the two statements? What do the findings imply for measurement and future research with agricultural users?

The analysis is exploratory. It does not measure actual system reliability, identify an intervention, establish a causal chain or support a national estimate. Sections 2 and 3 explain the theory and methods; Section 4 reports the results; Sections 5–7 interpret them and set out implications and limitations.

2. Literature Review and Theoretical Foundation

The literature links trust in AI to both the quality of an output and the institutions, people and data arrangements surrounding a service. This section develops those links and distinguishes hypothetical confidence from demonstrated reliability and enforceable protection.

2.1 AI advice and agricultural knowledge

AI-supported services can organise information, produce recommendations and interact with users in natural language. Their value depends on whether outputs fit a particular crop, soil, season, location and decision. A review of South Asian smallholder applications warns that claims of transformation have often advanced faster than evidence of farmer outcomes.[5] A service that presents a general recommendation as locally verified could encourage costly decisions, even when its language appears authoritative. Because the survey does not specify a named service or agronomic task, this study cannot assess the quality of actual advice.

Digital agriculture also raises questions about data control, access, power and the distribution of benefits. Farm-level operational data and identifiable personal information are not automatically the same thing; legal treatment depends on the nature of the data and the relevant facts. Research on agricultural data ethics argues that ownership, privacy, security and unequal bargaining power deserve attention alongside technical performance.[6]

2.2 Trust and regulatory protection

Trust involves a willingness to accept vulnerability based on expectations about another actor's competence, integrity or benevolence.[7] In a digital service, familiarity, performance, source clarity and the ability to obtain help may all shape reliance, while a high reported trust level does not prove that the advice is reliable. Trust should be calibrated: users need enough information to decide when to rely, verify or seek qualified assistance. Studies of automation distinguish trust in a system from its objective trustworthiness.[8]

Perceived regulatory protection is similarly distinct from legal compliance. It concerns what a respondent believes oversight, rules or remedies can accomplish. The survey's oversight item asks whether oversight can increase confidence; it does not measure whether an identified regulator currently supervises agricultural AI or whether a remedy works in practice. Likewise, the accountability item asks about willingness under a stated condition and does not measure actual behaviour.

Provider transparency and public oversight may complement one another. A user may know who supplied advice without having a practical remedy; conversely, an oversight framework may exist but be unfamiliar or difficult to access. A comparison of statements about these conditions provides a starting point for more precise investigation rather than proof that one

[5] Amar Singh, Vinod Kumar Shukla and Chatter Singh, 'From Pilots to Plots: A Critical Review of Artificial Intelligence for Smallholder Agriculture in South Asia' (2026) DOI: 10.1177/00307270261489284.

[6] Carbonell (n 3); Klerkx, Jakku and Labarthe (n 2).

[7] Mayer, Davis and Schoorman (n 4).

[8] John D Lee and Katrina A See, 'Trust in Automation: Designing for Appropriate Reliance' (2004) 46 Human Factors 50; Kevin Anthony Hoff and Masooda Bashir, 'Trust in Automation: Integrating Empirical Evidence on Factors That Influence Trust' (2015) 57 Human Factors 407.

form of governance is superior.

2.3 Technology acceptance and digital governance

UTAUT2 explains technology acceptance using constructs including performance expectancy, effort expectancy and facilitating conditions. It gives a useful vocabulary for discussing perceived usefulness and support, but the present questionnaire does not operationalise the full model, and its data do not test UTAUT2's structural paths.[9] In agricultural advisory services, perceived benefits and an available support channel may be relevant while not resolving whether advice is correct or responsibility is clear.

Trust Theory adds attention to vulnerability and reliance. A digital-governance perspective adds transparency, allocation of responsibility, oversight, data practices and accessible channels for addressing harm. These perspectives address different questions: a useful interface, a trusted provider and a functioning remedy are not equivalent. Integrating them conceptually encourages the design of distinct measurements rather than an unsupported combined scale.[10]

An important distinction is between regulation as a public institutional arrangement and accountability as a practical relationship. A user may recognise an accountable provider without knowing the legal basis of a remedy, or may support government oversight while being uncertain about whether a complaint will be resolved. Nor is oversight necessarily a single instrument: audit, licensing, information requirements and complaint resolution operate through different mechanisms. The AAR2 statement does not separate them. Treating it as proof of confidence in a named regulator would therefore exceed the measure.[11]

The analysis also distinguishes perceived protection from a respondent's legal knowledge. A positive response might express a general expectation that oversight is desirable; it does not demonstrate that the respondent knows which protections are currently available. Legal research can complement the survey by examining a specific service, its data flows, applicable legal provisions and actual complaint arrangements. That assessment cannot be substituted for the responses analysed here.

2.4 AI literacy and the measurement problem

AI literacy can include recognising incorrect outputs, verifying information and understanding bias or data risks.[12] The supplied items reflect self-reported awareness and practices, not an objective test of competence. Higher agreement with an awareness item may coincide with either greater confidence or greater caution, depending on context. The survey cannot determine the effect of education or the temporal order of these attitudes.

The AAR block includes source/provider clarity, oversight, local adaptation, reporting and accountability. The AFR block includes usefulness, responsibility, limitations, human help and rights information. These are conceptually related but do not necessarily reflect a single latent trait. Mixing them can obscure differences between provider characteristics and governance mechanisms. Item-level analysis avoids interpreting a

[9] Venkatesh, Thong and Xu (n 4).

[10] Mayer, Davis and Schoorman (n 4); Mark Bovens, 'Analysing and Assessing Accountability: A Conceptual Framework' (2007) 13 European Law Journal 447; Eastwood and others (n 2).

[11] Bovens (n 10).

[12] Davy Tsz Kit Ng and others, 'Conceptualizing AI Literacy: An Exploratory Review' (2021) 2 Computers and Education: Artificial Intelligence 100041; Duri Long and Brian Magerko, 'What Is AI Literacy? Competencies and Design Considerations' in Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (ACM 2020).

composite as a validated measure; further work should evaluate construct structure and item interpretation before latent modelling.[13]

2.5 Analytical expectations

The primary comparison considers the paired responses to AAR1, which states that clear sources and a responsible provider would increase trust, and AAR2, which states that regulatory oversight can increase confidence. Secondary comparisons consider AAR5 versus AAR2 and AFR3 versus AAR3. These are exploratory item comparisons and not pre-registered hypotheses. The correlation analysis examines three awareness or verification items against AAR1 and AAR2, with adjustment across six tests. It does not test whether regulation causes trust or whether AI literacy moderates an intervention.

3. Methodology

The methodology describes the available records, measurement decisions, participant safeguards and analysis. It preserves distinctions between the original intended rural focus and the actual population represented by the recorded categories.

3.1 Design and population

The study analyses a cross-sectional questionnaire. The unit is the individual response; no court, farm, provider or AI system is directly observed. Respondents are coded as law students, law graduates, advocates or legal professionals, and other relevant respondents. This mixed composition cannot establish that the sample consists of farmers, agricultural users or rural inhabitants. These limitations determine the scope of the title, results and discussion. Cross-sectional responses do not establish temporal sequence or causation.[14]

3.2 Sample and eligibility

The workbook contains 385 records, each coded as consenting, aged 18 or older and aware of AI. Respondent IDs are unique. The available file does not document dates, recruitment channels, sampling frame, response rate or completed duplicate-screening procedures. Consequently, the sample is not described as randomly selected or nationally representative. A sample-size planning target of 385 does not by itself establish the precision of estimates from an undocumented sampling design.[15]

The Codebook labels the respondent identifier sequence and contextual comments as synthetic. The researcher confirmed that the numerical survey responses were collected from actual participants. The creation and purpose of the identifier and comments remain to be documented; the optional contextual text was excluded. This distinction is retained in the article because it affects the reproducibility and provenance of the dataset.

[13] Godfred O Boateng and others, ‘Best Practices for Developing and Validating Scales for Health, Social, and Behavioral Research: A Primer’ (2018) 6 Frontiers in Public Health 149; Klaas Sijtsma, ‘On the Use, the Misuse, and the Very Limited Usefulness of Cronbach’s Alpha’ (2009) 74 Psychometrika 107.

[14] Erik von Elm and others, ‘The Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) Statement: Guidelines for Reporting Observational Studies’ (2007) 4 PLOS Medicine e296.

[15] William G Cochran, Sampling Techniques (3rd edn, John Wiley & Sons 1977).

3.3 Questionnaire and analytical items

The Codebook records five-point response options from strongly disagree to strongly agree. AAR1 combines clarity of sources and identification of a responsible provider; the components cannot be separated. AAR2 concerns the potential effect of regulatory oversight on confidence. AAR3 asks that recommendations be adapted locally; AAR4 concerns ways to report harm; AAR5 links strong accountability to willingness to use services. The statements do not measure the respondent's current level of trust in a particular system, nor do they specify a regulator or an intervention.

AFR2 concerns identifying responsibility, AFR3 concerns communication of uncertainty and limitations, and AFR4 concerns human help. The exploratory awareness items are AIL1, awareness of plausible inaccuracies; AIL2, reported verification; and AIL3, awareness of bias or incomplete data. Exact wording is included in Appendix A. The records do not document item-source adaptation, cognitive testing or a pilot; none is assumed.[16]

3.4 Data collection and screening

The dataset records eligibility and closed-ended responses, but the supplied materials do not establish the mode of administration, locations of recruitment, dates, invitations, exclusions or response rate. The focal numerical items contain no missing responses. We report current status and recorded location as provided, without inferring agricultural occupation or agricultural AI use. Optional contextual text is not used for analysis.

3.5 Statistical analysis

Item distributions are reported with counts and endorsement percentages, where endorsement means a response of agree or strongly agree. Neutral answers are included in non-endorsement and must not be classified as rejection. Pointwise Wilson intervals are descriptive uncertainty summaries and depend on sampling assumptions not established for this dataset.[17]

The three paired contrasts compare endorsement proportions within respondents, retaining discordant counts and using exact McNemar tests. Holm correction is applied across the three comparisons. Whole-record bootstrap percentile intervals describe uncertainty in each paired difference; they are pointwise, not multiplicity-adjusted. The statements differ in wording and scope, so a paired difference is not a direct preference ranking.[18]

Spearman rank correlations describe associations between AIL1–3 and AAR1–2, with Holm adjustment across the six exploratory tests. These are individual ordinal responses, not latent scores; coefficients do not imply direction of influence. Pointwise bootstrap intervals and adjusted p-values are presented separately. Lack of statistical evidence does not establish equivalence or absence of an association.[19]

The contrast of AAR1 with AAR2 uses the same persons, avoiding the error of treating their endorsement percentages as independent samples. The exact test concerns the numbers of respondents who endorse only one of the two statements; it does not test equality of two latent constructs. The bootstrap resamples complete respondent records to preserve that pairing. All confidence intervals remain conditional on the

[16] Boateng and others (n 13).

[17] Cochran (n 15).

[18] Quinn McNemar, 'Note on the Sampling Error of the Difference between Correlated Proportions or Percentages' (1947) 12 Psychometrika 153; Sture Holm, 'A Simple Sequentially Rejective Multiple Test Procedure' (1979) 6 Scandinavian Journal of Statistics 65; Bradley Efron and Robert J Tibshirani, An Introduction to the Bootstrap (Chapman & Hall 1993).

[19] Holm (n 18); Douglas G Altman and J Martin Bland, 'Absence of Evidence Is Not Evidence of Absence' (1995) 311 BMJ 485; Ronald L Wasserstein and Nicole A Lazar, 'The ASA Statement on p-Values: Context, Process, and Purpose' (2016) 70 American Statistician 129.

recorded sample and cannot correct unknown selection into the study. The six correlations similarly describe rank ordering of observed responses and are sensitive to the questionnaire's wording and response categories.

3.6 Measurement and data quality

No composite trust, AI literacy or regulatory-protection scale is claimed. The questionnaire groups items for a shared project, but conceptual heterogeneity means internal consistency alone would not establish a valid construct. Respondent categories may themselves be broad, especially "other relevant respondent," and the workbook does not show whether a person uses AI for agriculture. The analysis therefore avoids occupation-specific and agricultural-user claims.

3.7 Ethical considerations

Ethical approval for this study was obtained from the Center for Academic & Professional Career Development and Research (CAPCDR), an external institutional body, under approval reference CAPCDR: SMUCT/LLB/SS-0020260908-19. External ethical review was sought because Shanto-Mariam University of Creative Technology does not have an institutional ethics committee responsible for reviewing this type of research.

4. Results

The results describe the 385 records and compare distinct questionnaire statements. Counts reflect respondent endorsements rather than observed service performance or legally verified protection.

4.1 Sample composition

Table 1 summarises recorded current status and location. Neither field identifies farmers or confirms agricultural AI use.

Table 1. Recorded respondent status and location

Measure	Category	Count (%)
Status	Other relevant respondent	140 (36.4%)
	Law student	136 (35.3%)
	Law graduate	58 (15.1%)
	Advocate or legal professional	51 (13.2%)
Location	Dhaka	177 (46.0%)
	Other city corporation	78 (20.3%)
	District town	66 (17.1%)
	Upazila-rural area	60 (15.6%)
	Other	4 (1.0%)

N = 385. The categories reflect the original questionnaire; agriculture-related work and use of agricultural AI are not identified.

Of 385 respondents, 60 (15.6%) are in the upazila/rural location category, while 177 (46.0%) are in Dhaka. The location category is a single broad classification and should not be treated as a measure of rural residence alone. This distribution limits the original proposed focus on rural users.

4.2 Statements on trust and governance

Table 2 reports responses to the five AAR items, each of which addresses a different condition or safeguard.

Table 2. Trust-condition and governance responses

Item	Counts 1 / 2 / 3 / 4 / 5	Endorsed n (%)	95% CI (%)
AAR1	0 / 4 / 71 / 187 / 123	310 (80.5%)	76.3–84.2
AAR2	0 / 18 / 112 / 182 / 73	255 (66.2%)	61.4–70.8
AAR3	1 / 30 / 119 / 180 / 55	235 (61.0%)	56.1–65.8
AAR4	0 / 9 / 113 / 179 / 84	263 (68.3%)	63.5–72.8
AAR5	0 / 0 / 68 / 173 / 144	317 (82.3%)	78.2–85.8

N = 385. Endorsement means agree or strongly agree; non-endorsement includes neutral responses. Wilson intervals are pointwise. Appendix A gives exact wording.

Source and provider clarity was endorsed by 310 respondents (80.5%); the oversight statement by 255 (66.2%); and strong accountability increasing willingness by 317 (82.3%). Local

adaptation and a route to report harmful or inaccurate recommendations were endorsed by 235 (61.0%) and 263 (68.3%). These values describe agreement with hypothetical or normative statements and do not measure existing trust, actual oversight or service quality.

4.3 Agricultural-advice and safeguard statements

Table 3 presents the AFR items separately to clarify the relationship between views about usefulness and preferred service safeguards.

Table 3. Agricultural advice and safeguard responses

Item	Counts 1 / 2 / 3 / 4 / 5	Endorsed n (%)	95% CI (%)
AFR1	0 / 12 / 129 / 176 / 68	244 (63.4%)	58.5–68.0
AFR2	0 / 4 / 51 / 164 / 166	330 (85.7%)	81.9–88.9
AFR3	0 / 8 / 52 / 178 / 147	325 (84.4%)	80.5–87.7
AFR4	2 / 13 / 123 / 177 / 70	247 (64.2%)	59.2–68.8
AFR5	0 / 3 / 44 / 173 / 165	338 (87.8%)	84.1–90.7

N = 385. Endorsement means agree or strongly agree; non-endorsement includes neutral responses. Wilson intervals are pointwise. Appendix A gives exact wording.

Useful information was endorsed by 244 respondents (63.4%); provider responsibility by 330 (85.7%); communicating limitations by 325 (84.4%); access to human assistance by 247 (64.2%); and inclusion of legal-rights information by 338 (87.8%). These different statements are not equivalent tests of specific policy designs.

4.4 Paired comparisons and joint responses

Table 4 reports three within-respondent contrasts. Counts marked “first only” and “second only” describe respondents who endorsed one statement but not the other; the latter includes neutral responses.

Table 4. Paired endorsement contrasts

Contrast	First only / second only	Difference pp	95% CI pp	Holm p
AAR1 – AAR2	100 / 45	14.3	8.3–20.0	<.001
AAR5 – AAR2	101 / 39	16.1	10.4–22.1	<.001
AFR3 – AAR3	123 / 33	23.4	17.4–29.1	<.001

N = 385; pp = percentage points. Exact McNemar tests, Holm adjustment across three comparisons; 10,000 respondent-level bootstrap resamples, pointwise intervals. The statements have different wording.

Source/provider clarity exceeded the oversight statement by 14.3 percentage points. Accountability exceeded oversight by 16.1 points. Communication of uncertainty exceeded local adaptation by 23.4 points. Each contrast remained statistically distinguishable after Holm correction, but the paired statements have different wording and do not establish which safeguard would be more effective in practice.

Table 5 displays the joint endorsement pattern for source/provider clarity and regulatory oversight.

Table 5. Joint endorsement of clarity and oversight

Response configuration	Count (%)
Both endorsed	210 (54.5%)
Clarity only	100 (26.0%)
Oversight only	45 (11.7%)
Neither endorsed	30 (7.8%)

N = 385. Neither includes neutral and disagreement; these are not fixed respondent types.

A total of 210 respondents (54.5%) endorsed both; 100 (26.0%) endorsed only clarity, and 45 (11.7%) endorsed only oversight. The remaining 30 (7.8%) endorsed neither. This descriptive pattern indicates that both conditions can coexist in one respondent’s answers; non-endorsement should not be described as opposition.

4.5 Exploratory correlations with awareness

Table 6 presents six rank correlations between three AI-awareness or verification statements and the two trust-related conditions. The multiple-testing correction applies to the six p-values, while bootstrap intervals are pointwise.

Table 6. Exploratory awareness and trust-condition associations

Items	Spearman ρ	95% CI	p	Holm p
AIL1 / AAR1	0.187	0.095–0.277	<.001	0.001
AIL1 / AAR2	0.057	-0.042–0.156	0.263	1.000
AIL2 / AAR1	0.041	-0.062–0.144	0.426	1.000
AIL2 / AAR2	0.050	-0.044–0.145	0.331	1.000
AIL3 / AAR1	0.143	0.041–0.240	0.005	0.025
AIL3 / AAR2	0.045	-0.057–0.148	0.382	1.000

N = 385. Pointwise percentile intervals from 2,000 respondent-level bootstrap resamples; p-values Holm adjusted across six tests. Intervals are not adjusted for multiplicity.

Awareness that AI can produce plausible inaccuracies (AIL1) had a small positive association with the source/provider clarity item (ρ = .187; Holm p = .001), as did awareness of bias or incomplete data (AIL3; ρ = .143; Holm p = .025). Neither item showed clear evidence of association with the oversight item after correction; the verification item was not clearly associated with either outcome. These findings are exploratory and their interpretation is constrained by the different content of the statements, self-report, simultaneous measurement and the non-representative sample. An association does not establish that awareness causes confidence or that training would change reliance. In particular, the questionnaire does not specify an actual regulatory authority, service or decision outcome.

5. Discussion

The findings separate provider-level transparency from institutional oversight and other governance preferences. They also show why hypothetical agreement needs to be interpreted within the questionnaire and sample rather than as evidence of actual agricultural service experience.

5.1 Source clarity and oversight

Most respondents endorsed the statement about clearer sources and a responsible provider, and a smaller proportion endorsed the oversight statement. A paired contrast confirms the difference in response distributions within this sample. The items, however, use different language: one asks about a personal increase in trust under specified conditions, and the other makes a general proposition that oversight can increase confidence. Different scope, familiarity and wording may contribute to the difference. A survey cannot determine those explanations. Nor can it establish whether identifiable providers or regulators actually protect users.

This finding suggests a measurement agenda rather than a governance ranking. Provider identity, independently verified sources, effective oversight and accessible remedy should be tested as separate attributes of a defined service. Research on digital agriculture emphasises that trust depends on data practices and institutional arrangements as well as technical properties.[20]

[20] Bhattarai and others (n 1); Klerkx, Jakku and Labarthe (n 2).

5.2 Accountability and redress

A large majority endorsed the statement linking accountability with willingness to use agricultural AI. This is a conditional self-report, not observed adoption. The questionnaire does not define who is accountable, what obligations apply or how a user would obtain redress. Strong accountability could mean a responsive provider, independent oversight, enforceable rights or a combination of mechanisms. A follow-up study should specify the organisation, process, response time and remedy before testing their effects.

The reporting item addresses a necessary practical issue: a user must be able to identify an inaccurate or harmful recommendation and reach a body able to act. Reporting alone does not establish that a complaint will be resolved or that compensation will be available. In a consequential agricultural decision, a meaningful process would require a clear record of what advice was given, what limitations were disclosed and which human or institution is responsible.[21]

5.3 Local adaptation and uncertainty

Respondents endorsed communication of uncertainty more frequently than local adaptation. This difference does not show that one is more important: the first item describes what a service should communicate, while the second specifies how recommendations should be adapted. Both can be necessary. A statement of uncertainty is useful only if users can understand and act on it; localisation is valuable only if the local data and agronomic guidance are appropriate for the task. A real evaluation should therefore test accuracy and communication together across crops, seasons and locations.[22]

5.4 Awareness and reliance

The two small positive associations between risk-awareness items and the source/provider clarity statement suggest a question for further study: whether people who recognise possible output failures give particular attention to identifying a source. Neither item was clearly associated with the oversight statement after correction. These patterns do not establish that the relationships differ across outcomes; a formal comparison would be required. The correlation analysis examines self-reported awareness of inaccurate outputs and bias, and a reported verification practice. Such items do not constitute a validated literacy test. Even an observable association with a trust condition would not establish whether awareness preceded confidence, whether a third factor shaped both, or whether a training programme would alter decision-making. The sample includes respondents with diverse legal and other backgrounds, whose interpretations of agricultural AI may differ.[23]

Trust in a hypothetical agricultural service is not a demonstrated willingness to rely on advice about pesticide application, planting or a costly input. Experimental vignettes and observed verification tasks could provide clearer evidence about how users respond to source information, local evidence and the possibility of human review. A comparative design should include farmers, extension workers and affected rural communities, with sampling and recruitment documented.

[21] Bovens (n 10); Eastwood and others (n 2).

[22] Singh, Shukla and Singh (n 5); Bhattarai and others (n 1).

[23] Ng and others (n 12); Wasserstein and Lazar (n 19).

5.5 Bangladesh law and institutional context

Bangladesh's Personal Data Protection Act 2026 supplies a potential legal context when a digital service processes identifiable personal data. Its applicability depends on the data, actors, legal provisions and commencement arrangements; the survey does not establish compliance, a breach or a specific obligation for a particular agricultural AI service.[24] Farm-related information should not automatically be assumed to be personal data, and the legal consequences of a given processing activity require a fact-specific assessment.

Respondents may use the word "regulatory" to mean rules, oversight, professional guidance or a complaint mechanism. The questionnaire does not identify a particular authority, and no specific protection can be inferred from agreement with AAR2. Future work should explain the relevant law and institutions to participants and measure their ability to use available mechanisms, rather than relying only on a general statement of confidence.

Comparing the two source-related awareness correlations with the two oversight correlations also illustrates the value of defining an outcome. Awareness that AI may give inaccurate information has a clearer descriptive connection with the source/provider statement than with the broad oversight statement, but the study has not tested the difference between these two coefficients. A difference in their p-values alone cannot demonstrate that the correlations differ. Further studies should compare them directly and specify the causal or predictive question before analysis.[25]

The location data require equally careful use. Upazila and rural areas form one combined category, so membership does not by itself demonstrate farming status, residence in a village or use of an AI advisory application. The remaining categories include Dhaka, other city corporations, district towns and other locations. Sampling respondents from varied locations can be valuable, but the design must explicitly state whose perceptions the study aims to represent. In this file the occupation categories are legal and other rather than agricultural, so rural service recommendations are prospective rather than direct findings from farmers.

5.6 Integrated interpretation

UTAUT2 highlights perceived usefulness and support, while Trust Theory directs attention to reliance under uncertainty. Digital governance draws attention to mechanisms that make responsibility and correction possible. These perspectives complement each other, but the present study does not validate the integrated model or test moderation. Its empirical contribution is to show that clear-provider, oversight, accountability and local-adaptation items produce distinguishable distributions in a mixed sample.[26]

6. Theoretical and Practical Implications

The implications below are grounded in the reported item-level responses and relevant research. They are proposals for service design and future evaluation, not demonstrated effects of the stated safeguards.

[24] Personal Data Protection Act 2026 (Bangladesh Act No 63 of 2026), s 1.
[25] Altman and Bland (n 19); Wasserstein and Lazar (n 19).
[26] Venkatesh, Thong and Xu (n 4); Mayer, Davis and Schoorman (n 4).

6.1 Theoretical implications

First, trust in agricultural AI should be separated from the conditions a respondent believes could increase trust. AAR1 and AAR5 ask conditional questions; neither gives a baseline level of trust. Second, provider transparency and regulatory oversight should be measured separately because they describe different institutions and responsibilities. The paired distribution supports that analytical distinction but does not prove that the two mechanisms have different effects.

Third, the results illustrate why technology-acceptance constructs must be adapted to a concrete task. A general belief that agricultural AI could be useful may coexist with demands for accountability and human help. A validated follow-up instrument could measure perceived competence, integrity, institutional safeguards, trust and intended reliance separately, then examine their relationships without treating a heterogeneous item block as a single scale.[27]

6.2 Practical and policy implications

Providers could identify the organisation responsible for the service, disclose relevant sources and the date or limits of the information, and present uncertainty in a language and format suitable for the intended audience. They could also test recommendations against local agronomic evidence and provide a functioning route to qualified human help. These actions require local testing and should not be represented as guaranteed to increase trust or improve farm outcomes.

Policymakers and extension organisations can assess the accessibility of complaints, the allocation of responsibilities and data protection in the relevant service context. A digital form alone may not be usable where connectivity, literacy or language is a barrier. Testing should include real users with different access conditions, and any legal compliance assessment should identify the applicable rules and facts.[28]

An operational evaluation could begin with several concrete questions: whether an advisory answer identifies its source and publication date; whether a user can recognise its limitations; whether an appropriately trained person can review a high-consequence recommendation; and whether an incorrect answer can be reported without excessive cost or delay. These questions translate the article's conceptual categories into observable features. Service-specific audits would still need to assess accuracy, inclusion and local relevance rather than assume that disclosure alone makes advice safe.[29]

7. Conclusion, Limitations and Future Research

In this 385-record mixed sample, 80.5% endorsed the statement that clear sources and a responsible provider would increase trust, 66.2% endorsed the statement that regulatory oversight can increase confidence, and 82.3% endorsed the accountability statement. The source/provider clarity item exceeded oversight by 14.3 percentage points, with 210 respondents endorsing both. Because these are different hypothetical statements, the findings do not establish the comparative effectiveness of governance measures.

The study is limited by cross-sectional self-report, incomplete recruitment and fieldwork documentation, uncertain sampling design and heterogeneous questionnaire content. Only 60 respondents are recorded in the broad upazila/rural location category, and agricultural occupation and actual use of agricultural AI are not identified. The Codebook labels identifiers and contextual comments synthetic, while the research team confirms actual numerical survey

[27] Mayer, Davis and Schoorman (n 4); Boateng and others (n 13).
[28] Eastwood and others (n 2); Carbonell (n 3).
[29] Bhattarai and others (n 1); Eastwood and others (n 2).

responses; the source and transformation of these fields should be documented. No national, farmer-specific or causal claim follows from this dataset.

Future work should recruit and identify agricultural users transparently, document location and fieldwork procedures, and distinguish actual agricultural service experience from general AI awareness. A scenario experiment could vary provider identity, source documentation, oversight, local validation and an accessible complaint mechanism. Interviews and behavioural tasks could examine whether users understand and act on these features. Independently evaluated agronomic outcomes would provide evidence about accuracy and suitability that a perception survey cannot supply.

Declarations

Ethical approval and oversight

Ethical approval for this study was obtained from the Center for Academic & Professional Career Development and Research (CAPCDR), an external institutional body, under approval reference CAPCDR: SMUCT/LLB/SS-0020260908-19. External ethical review was sought because Shanto-Mariam University of Creative Technology does not have an institutional ethics committee responsible for reviewing this type of research.

Informed consent

Informed consent was obtained from adult participants before questionnaire completion. The questionnaire explained the study purpose, voluntary participation, anonymity and the option to discontinue. All analysed records contain affirmative consent and adult-eligibility responses.

Data availability

The numerical data supporting the reported analyses are held by the research team. Requests for de-identified data and analytical specifications may be directed to the corresponding author. Any sharing is subject to participant confidentiality and applicable institutional requirements. The contextual-text field was excluded from the analysis.

Conflict of interest

The authors declare that they have no conflicts of interest.

Author contributions

Md. Nasim: Lead student researcher; conceptualisation; preparation of study materials; organisation and curation of survey data; manuscript development. The project was conducted under the supervision of Prof. Dr Kazi Abdul Mannan.

Kazi Abdul Mannan: Conceptual and methodological guidance; supervision; interpretation of statistical findings; critical review and editing of the manuscript.

Generative AI disclosure

Generative AI assisted manuscript drafting, language editing, organisation and the development of analytical code. Statistical estimates were computed programmatically from the numerical survey data. Responsibility for the study's analysis, interpretation and reporting rests with the authors.

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Appendix A. Analytical questionnaire items

Table A1 reproduces the statements used in the analysis so that each estimate can be read against the original question wording.

Table A1. Exact wording of the analytical items

Code	Statement
AAR1	I would trust AI agricultural information more if its sources and responsible provider were clear.
AAR2	Regulatory oversight can increase confidence in digital agricultural services.
AAR3	AI agricultural recommendations should be adapted to local conditions rather than applied blindly.
AAR4	Users should have ways to report harmful or inaccurate recommendations.
AAR5	Strong accountability increases my willingness to use AI agricultural services.
AFR1	AI agricultural advisory services can help farmers access useful information.
AFR2	Farmers should know who is responsible for important advice delivered through AI systems.
AFR3	AI advisory services should clearly communicate uncertainty and limitations.
AFR4	Farmers should have access to human assistance when AI advice is inadequate.
AFR5	Legal-rights information should be incorporated into responsible digital agricultural services.
AIL1	I understand that generative AI can produce plausible but inaccurate information.
AIL2	I verify important AI-generated information before relying on it.
AIL3	I understand that AI outputs may reflect bias or incomplete data.

Source: Group 16 Codebook. Responses use five categories from strongly disagree to strongly agree.

The items are analysed separately; their presence in one block does not establish a single latent construct.

Table of legislation

Personal Data Protection Act 2026 (Bangladesh Act No 63 of 2026)