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Research Article

Farmers Rights Information and Safeguards in AI Agricultural Advisory Services in Bangladesh

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ABSTRACT

AI-supported agricultural advice raises questions about useful information, the responsibilities of providers and the accessibility of legal-rights information. This study examines stated preferences about these issues in 385 adult, AI-aware survey records from Bangladesh. The mixed sample consists of law students, graduates, legal professionals and other respondents; the workbook does not identify farmers, agricultural AI users or actual knowledge of farmers' legal rights. The analysis therefore examines questionnaire responses about rights information and safeguards rather than claiming to measure farmers' rights awareness or the effects of an AI service. Individual items are reported using descriptive distributions, paired comparisons and exploratory rank correlations with Holm adjustment. Of 385 respondents, 338 (87.8%) endorsed including legal-rights information in responsible digital agricultural services, 330 (85.7%) endorsed identifying responsibility for important advice, 325 (84.4%) endorsed communicating uncertainty and limitations, and 247 (64.2%) endorsed human assistance when AI advice is inadequate. The rights-information item exceeded the usefulness item by 24.4 percentage points; 215 respondents endorsed both. The statements differ in content, and their paired comparison does not identify the effects of a service or rank the value of its features. Exploratory correlations with the rights-information item were small and did not provide clear evidence of association after adjustment for four tests. The article distinguishes information about rights from demonstrated legal knowledge and recommends evaluation with identified agricultural users, specific legal scenarios and observable referral pathways.

Keywords: agricultural advisory services; farmers' rights; AI governance; legal information; human assistance; Bangladesh

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1. Introduction

Agricultural information can influence decisions about crops, inputs, water, pests and markets. Digital and AI-supported advisory services may make some information easier to obtain, but answers must be relevant to the user's crop, locality, resources and decision. Incorrect or incomplete recommendations can have practical consequences. Recent reviews of agricultural AI identify reliability, data governance, digital access and explainability as interconnected concerns.[1]

Rights information is a further part of responsible service design. An agricultural user may need to know what data a service collects, who is responsible for advice, whether a human can help and where a complaint may be directed. A general recommendation to include rights information does not establish which legal rights apply to a particular user or whether an available remedy works. Farm-related information is not automatically personal data; its legal treatment depends on whether it identifies a person and on the relevant legal context.[2]

The original study proposal asks whether AI agricultural advisory services improve farmers' legal-rights awareness. The supplied questionnaire, however, asks whether legal-rights information should be incorporated into responsible services; it does not test respondents' knowledge of specific rights or observe a change in awareness after using an AI service. The available status categories also do not identify farmers or actual agricultural AI users. A claim that AI caused farmers to understand their rights would therefore go beyond the data.

This article investigates a more precise question: how do respondents endorse rights-information and accountability statements alongside statements about usefulness and human assistance? Its contribution is to distinguish an informational safeguard from both demonstrated legal knowledge and observed use. It uses the same Group 16 data as related research but focuses specifically on rights-information inclusion, responsibility and human help rather than treating trust or general AI literacy as the primary outcome.

The objectives are to describe the recorded sample and agricultural-advisory items, compare selected statements within respondents, and explore associations with endorsement of rights-information inclusion. The research questions are: How often are rights information, provider responsibility, uncertainty disclosure and human assistance endorsed? How does support for rights information coexist with perceived usefulness? How is rights-information endorsement associated with selected usefulness, reporting, data-transparency and AI-awareness items? What additional measures would be needed to study actual legal empowerment?

The recorded sample includes law students, graduates, legal professionals and other respondents. It is not presented as representative of farmers or rural users in Bangladesh. Section 2 develops the conceptual and legal context; Section 3 explains the data and analysis; Section 4 reports results; and Sections 5-7 discuss implications and limitations.

[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] Isabelle M Carbonell, 'The Ethics of Big Data in Big Agriculture' (2016) 5(1) Internet Policy Review, DOI: 10.14763/2016.1.405; Personal Data Protection Act 2026 (Bangladesh Act No 63 of 2026), s 2.

2. Literature Review and Theoretical Foundation

Research on digital agriculture links advisory quality to information sources, local suitability, data governance and the ability of users to obtain help. This section distinguishes these service features from the legal knowledge and outcomes that an effective rights-based assessment would need to measure.

2.1 AI advisory services and legal information

AI-supported advisory services can generate or organise information about agricultural questions. Their usefulness depends on whether information is accurate and appropriate to a particular location, crop, season and user. A review of smallholder AI in South Asia cautions that claims about transformation have advanced faster than evidence on farmer outcomes.[3] The present questionnaire does not identify a tool or test the quality of any recommendation.

Digital agricultural information also involves questions of responsibility and control of data. Scholarship on digital agriculture describes possible asymmetries between users, technology providers and other organisations that collect or use information.[4] A service might explain its own data practices, but a rights-based approach also asks whether the user can understand applicable rights and seek an effective response when a problem arises.

2.2 Rights information, knowledge and empowerment

The rights-information item asks whether legal-rights information should be incorporated into responsible digital agricultural services. Agreement with that statement is a service preference, not evidence that a respondent knows the legal content of the information, that a service has supplied it, or that a farmer can exercise a right. These distinctions matter because legal empowerment involves more than access to a general statement: it may require understanding a specific entitlement, identifying a responsible actor, obtaining advice and using a practical remedy.

An evaluation could present a defined scenario, identify which information the system gives, and test whether a participant understands the next available step. It could separately assess whether a referral works. The current instrument contains no such test, baseline or follow-up. The title and interpretation therefore refer to rights information and safeguards rather than a demonstrated increase in legal awareness.

[3] 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.

[4] 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; Carbonell (n 2).

2.3 Trust, responsibility and human assistance

The questionnaire asks whether farmers should know who is responsible for important AI advice, whether uncertainty and limitations should be communicated, and whether human help should be available when advice is inadequate. These are related aspects of accountability but are not interchangeable. A named provider may not make a response accurate; disclosure of uncertainty may not give the user access to a qualified person; and a human-help link is not evidence that help can actually be obtained.

Trust Theory describes willingness to rely on another actor under uncertainty.[5] Trust should be calibrated to evidence and service conditions, not inferred solely from a user's support for transparency. A recent review of agricultural AI highlights data governance, skills, explainability, reliability and cost as connected influences on trust and adoption.[6] Its cross-context synthesis provides a research agenda, not a direct finding about the participants in this workbook.

2.4 Theoretical framework

UTAUT2 provides concepts such as expected usefulness, effort and facilitating conditions.[7] Trust Theory addresses reliance under uncertainty, while a digital-governance perspective examines responsibility, data practices and routes for correction or redress.[8] These approaches are complementary: perceived usefulness does not itself show that legal information is correct, and support for governance does not establish whether a service is accessible.

The present questions do not operationalise the full UTAUT2 model or measure a validated legal-empowerment construct. The study does not estimate structural paths or moderation and does not claim to validate the theories. It uses them as interpretive perspectives for a descriptive, item-level analysis.

2.5 Bangladesh legal context

Bangladesh's Personal Data Protection Act 2026 supplies part of the legal context when a service processes identifiable personal information. The Act defines personal data and includes provisions concerning correction and security, subject to its scope, commencement and applicable legal conditions.[9] Not all farm information is automatically identifiable personal data, and the questionnaire does not identify a data controller, establish compliance or demonstrate a breach. Whether particular rights or duties apply requires the facts of the processing activity and the relevant provisions.

Farmers' legal rights may involve matters beyond data protection. The questionnaire does not identify a particular land, agricultural-input or contractual issue, so this article does not assert a specific additional entitlement from a general survey answer. Future research should identify the legal topic, applicable rules and a route for obtaining help before assessing rights awareness.

[5] Roger C Mayer, James H Davis and F David Schoorman, 'An Integrative Model of Organizational Trust' (1995) 20 Academy of Management Review 709.

[6] Bhattarai and others (n 1).

[7] 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.

[8] Mayer, Davis and Schoorman (n 5); 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.

[9] Personal Data Protection Act 2026 (Bangladesh Act No 63 of 2026), s 1; Personal Data Protection Act 2026 (n 2); Personal Data Protection Act 2026 (Bangladesh Act No 63 of 2026), s 12; Personal Data Protection Act 2026 (Bangladesh Act No 63 of 2026), s 17.

2.6 Analytical expectations and measurement

The AFR items cover usefulness of advisory information, responsibility, uncertainty disclosure, human assistance and inclusion of rights information. The AAR and ADG items cover related but distinct questions about reporting and data-use transparency. Their breadth means that averaging them into a single scale would require a defensible measurement model. Internal consistency alone would not establish construct validity.[10]

Three exploratory paired comparisons examine the rights-information item against usefulness, provider responsibility against human assistance, and rights information against human assistance. Four exploratory rank correlations examine rights-information responses in relation to usefulness, reporting, transparent data-use practices and awareness of AI inaccuracies. The supplied materials do not establish a preregistered test family. The analyses do not measure an intervention or a change in knowledge.

3. Methodology

This section explains the recorded sample, the meanings and limits of the questionnaire items, ethics safeguards and statistical analysis. It distinguishes a stated service preference from observed agricultural use and legal knowledge.

3.1 Design and study population

The study analyses a cross-sectional questionnaire. The unit is an individual record; no farm, advice system, legal case, referral or legal outcome is observed. Respondent-status categories comprise law students, law graduates, advocates or legal professionals and other relevant respondents. The workbook does not identify farmers or verify whether respondents used agricultural AI. Accordingly, the sample is not described as representative of rural farmers or all users of agricultural services.[11]

3.2 Sample, eligibility and provenance

The workbook contains 385 records, each coded as consenting, adult eligible and AI-aware; respondent IDs are unique. The supplied files do not document the recruitment dates, sampling frame, invitations, response rate or independent duplicate-screening procedures. A target of 385 can arise from a conventional sample-size calculation under specified assumptions, but it does not establish random selection or a national margin of error.[12]

The researcher identified the numerical answers as real survey responses. The Codebook labels the respondent identifier sequence and optional contextual comments as synthetic. Their preparation and relationship to source records should be documented; contextual text was excluded from analysis. These labels do not independently establish the origin of numerical data, so fieldwork and consent documentation remain important.

[10] 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.

[11] 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.

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

3.3 Questionnaire and analytical items

All focal items use five response categories from strongly disagree to strongly agree. AFR1 asks whether AI agricultural advisory services can help farmers access useful information. AFR2 concerns knowing who is responsible for important advice; AFR3 concerns communication of uncertainty and limitations; AFR4 asks for human assistance when advice is inadequate; and AFR5 concerns incorporating legal-rights information in responsible services.

The exploratory associations use AAR4, which concerns ways to report harmful or inaccurate recommendations; ADG2, which describes confidence under transparent data-use practices; and AIL1, which concerns awareness of plausible but inaccurate AI information. Exact wording appears in Appendix A. The items express attitudes or stated awareness, not objective legal knowledge, observed service use or actual data practices. No pilot, adapted scale or validation procedure is asserted without documentation.[13]

3.4 Data collection and screening

The focal numerical items contain valid answers for the 385 supplied records. The workbook codes eligibility and consent but does not establish administration mode, fieldwork dates, invitations, exclusions or response rate. Status and location are reported as recorded without inferring agricultural occupation or experience with an AI advisory service. Optional contextual text is not analysed.

3.5 Statistical analysis

For each item, the distribution and number endorsing agree or strongly agree are reported. Neutral responses are included in non-endorsement and are not treated as opposition. Pointwise Wilson intervals describe uncertainty under conventional assumptions that are not secured by an undocumented sampling design; they should not be interpreted as national estimates.[14]

Three within-person contrasts compare AFR5 with AFR1, AFR2 with AFR4, and AFR5 with AFR4 using exact McNemar tests and Holm adjustment across the three tests. Whole-record bootstrap percentile intervals preserve pairing and are pointwise. Different wording means a paired difference is not a direct ranking of service features or their causal effectiveness.[15]

Four exploratory Spearman correlations compare AFR5 with AFR1, AAR4, ADG2 and AIL1. Holm correction covers the four p-values; percentile bootstrap intervals remain pointwise. The items are ordinal responses measured at the same time and are not latent scores. A non-significant association does not establish that a relationship is absent, and no estimate identifies the effect of an advisory intervention on knowledge or behaviour.[16]

[13] Boateng and others (n 10).

[14] Cochran (n 12).

[15] 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).

[16] Holm (n 15); 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.

3.6 Measurement limitations

The AFR5 item does not ask participants to name a specific right, apply a law or report receiving rights information. AFR2 and AFR4 ask for different safeguards; support for one does not show that another is unnecessary. Opportunities to obtain human help, report errors or access a data notice may vary by service and setting, none of which is specified in the dataset. Self-report, common item context and unknown selection into the sample may affect the observed associations.[17]

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-0020260908-20. 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 responses in the 385 supplied records. They concern stated preferences and perceptions rather than measured awareness of legal rights among farmers or the effects of a deployed AI service.

4.1 Respondent profile

Table 1 shows the recorded status and location categories. Neither variable identifies farmers or agricultural AI users.

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. Status and location are reported as recorded; farming and agricultural AI use are not identified.

The records include 140 other relevant respondents (36.4%), 136 law students (35.3%), 58 law graduates (15.1%) and 51 advocates or legal professionals (13.2%). The upazila/rural category contains 60 respondents (15.6%) and does not separately identify rural residence or agricultural occupation.

4.2 Advisory information and safeguards

Table 2 reports the five AFR items separately. They measure views about useful information and different service safeguards, not a validated legal-awareness scale.

Table 2. Agricultural advisory and rights-information items

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. Endorsed means agree or strongly agree. Non-endorsement includes neutral responses. Wilson intervals are pointwise; exact wording is in Appendix A.

[17] Philip M Podsakoff and others, ‘Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies’ (2003) 88 Journal of Applied Psychology 879; Sijtsma (n 10).

Rights-information inclusion was endorsed by 338 respondents (87.8%), knowing the responsible provider by 330 (85.7%) and communication of uncertainty by 325 (84.4%). Human help when AI advice is inadequate was endorsed by 247 (64.2%), while 244 (63.4%) endorsed the usefulness statement. Different statements and response contexts prevent treating these percentages as a direct ranking of respondents' needs.

4.3 Reporting and data-use context

Table 3 presents the additional AAR4, ADG2 and AIL1 items used in the exploratory analysis. These items describe an anticipated reporting route, conditional confidence and self-reported awareness respectively.

Table 3. Reporting, data-use transparency and AI awareness

Item	Counts 1 / 2 / 3 / 4 / 5	Endorsed n (%)	95% CI (%)
AAR4	0 / 9 / 113 / 179 / 84	263 (68.3%)	63.5-72.8
ADG2	0 / 5 / 59 / 167 / 154	321 (83.4%)	79.3-86.8
AIL1	3 / 34 / 131 / 157 / 60	217 (56.4%)	51.4-61.2

N = 385. Endorsed means agree or strongly agree. Non-endorsement includes neutral responses. Wilson intervals are pointwise; exact wording is in Appendix A.

Ways to report harmful or inaccurate recommendations were endorsed by 263 respondents (68.3%), confidence under transparent data-use practices by 321 (83.4%), and awareness that AI can produce plausible inaccuracies by 217 (56.4%). Endorsement does not establish that a reporting channel or transparent data policy exists for an actual service.

4.4 Paired endorsement and joint responses

Table 4 compares three selected item pairs within the same respondents. The differences should be read with the item wording and the pointwise intervals.

Table 4. Paired endorsement comparisons

Contrast	First only / second only	Difference pp	95% CI pp	Holm p
AFR5 - AFR1	123 / 29	24.4	18.7-30.4	<.001
AFR2 - AFR4	118 / 35	21.6	15.6-27.5	<.001
AFR5 - AFR4	115 / 24	23.6	18.2-29.1	<.001

N = 385; pp = percentage points. Exact McNemar tests; Holm adjustment across three tests. Intervals are pointwise percentiles from 10,000 respondent-level bootstrap resamples. Items differ in wording.

Rights-information inclusion exceeded the usefulness statement by 24.4 percentage points; provider responsibility exceeded human assistance by 21.6 points; and rights information exceeded human assistance by 23.6 points. The adjusted tests describe different response distributions. They do not establish the relative effectiveness of any service feature, and neutral answers are included in non-endorsement.

Table 5 shows the joint distribution of rights-information and usefulness endorsements. The categories represent answer combinations rather than fixed types of respondents.

Table 5. Joint endorsement of rights information and usefulness

Response configuration	Count (%)
Both endorsed	215 (55.8%)
Rights information only	123 (31.9%)
Usefulness only	29 (7.5%)
Neither endorsed	18 (4.7%)

N = 385. Neither includes neutral responses; categories describe answer combinations, not fixed respondent types.

A total of 215 respondents endorsed both statements, while 123 endorsed the rights-information statement without endorsing the usefulness statement. This pattern does not show whether rights information changes perceptions of usefulness or whether the respondent has used an advisory service.

4.5 Exploratory associations

Table 6 presents four Spearman rank correlations with AFR5. The four p-values are Holm adjusted; confidence intervals are pointwise and are not adjusted for multiplicity.

Table 6. Exploratory associations with rights-information endorsement

Items	Spearman ρ	95% CI	p	Holm p
AFR5 / AFR1	0.047	-0.053-0.149	0.356	0.923
AFR5 / AAR4	0.052	-0.049-0.154	0.308	0.923
AFR5 / ADG2	0.019	-0.086-0.117	0.703	0.923
AFR5 / AIL1	0.095	-0.003-0.192	0.064	0.254

N = 385. Four correlation p-values Holm adjusted. Pointwise percentile intervals use 2,000 respondent-level resamples and are not adjusted for multiplicity.

The estimated correlations are small and none provides clear evidence against a null association after adjustment. The results do not prove that service usefulness, reporting, transparency or awareness are unrelated to rights-information preferences. The questionnaire cannot establish whether a change in any of these factors would affect legal knowledge or a person's ability to use a remedy.

5. Discussion

The findings separate support for legal-rights information from perceived usefulness and other safeguards. Their interpretation is limited to the questionnaire responses and the mixed sample, not measured outcomes among farmers.

5.1 Rights information and useful advice

A substantial majority endorsed including legal-rights information in responsible services. The usefulness item received a lower endorsement, and 215 respondents endorsed both. These patterns are consistent with the possibility that respondents can view rights information and useful advice as distinct features, but the items are not a forced-choice test. Differences in wording, specificity or assumptions about agricultural AI could contribute to their distributions.

The survey does not test whether information is legally accurate, understandable or actionable. A system that displays a generic statement about rights may still leave a user unable to identify an applicable rule or obtain help. Future evaluations should specify the rights issue and measure comprehension, appropriate referral and the user's ability to act. A broader digital-agriculture literature emphasises the importance of accountability and power over data and service design.[18]

[18] Klerkx, Jakku and Labarthe (n 4); Carbonell (n 2).

5.2 Responsibility and human assistance

The provider-responsibility statement attracted more endorsement than the human-assistance statement. This does not establish that respondents value a named provider more than access to a person: one item asks who is responsible for advice and the other specifies help when advice is inadequate. Both can be necessary, and the questionnaire does not explain how they would be implemented.

A meaningful human-help pathway should identify who can respond, the type of question they can address, any cost or delay, and what happens if the problem is outside their expertise. It should not depend solely on a label that an AI tool is supervised. Responsible service evaluation requires evidence about whether a user actually reaches an appropriate person.[19]

5.3 Data transparency, reporting and legal context

The exploratory association between rights-information endorsement and the transparent-data-use statement was small and uncertain after adjustment. The same is true of the relationship with the reporting item. The findings cannot be used to claim that transparency or reporting has no relationship with legal-information preferences. They also cannot show that either safeguard causes awareness or that a remedy works.[20]

The Personal Data Protection Act 2026 is relevant where information is identifiable personal data and the relevant legal provisions apply. Its definitions and rules cannot be applied to an unspecified service without knowing the data flows and actors.[21] A legal-information feature should identify its legal scope and date, explain limitations, and offer a route to qualified assistance rather than treating every agricultural record as personal data.

5.4 Mixed sample and experience

The sample includes law students, graduates, legal professionals and other respondents. Only 60 records are coded in the combined upazila/rural category; that category does not independently identify farmers or rural residence. Participants may have different knowledge and experience of agriculture or digital services, and the file does not identify actual agricultural AI use. Accordingly, the results should not be described as farmers' legal knowledge, a rural population estimate or an evaluation of a service.

The numerical records were identified by the researcher as real survey data, while the Codebook labels identifiers and optional comments synthetic. Documentation should explain the creation of those fields and the relationship between the workbook and the source responses. Fieldwork dates and recruitment procedures are also needed for readers to assess selection and reproducibility.

5.5 Interpreting small associations

The four rank correlations with rights-information endorsement were small and none remained distinguishable from zero under the chosen Holm adjustment. The intervals allow a range of possible relationships, and lack of statistical evidence is not evidence of no effect. The items are individual, cross-sectional responses and do not provide a test of the proposed structural model.[22]

The questionnaire does not directly measure the effect of a service on farmers' rights awareness. The item-level results should therefore be interpreted as stated perceptions, with inferences limited to the measures actually collected.

[19] Eastwood and others (n 8); Bhattarai and others (n 1).
[20] Altman and Bland (n 16); Wasserstein and Lazar (n 16).
[21] Personal Data Protection Act 2026 (n 2); Personal Data Protection Act 2026 (n 9); Personal Data Protection Act 2026 (n 9).
[22] Wasserstein and Lazar (n 16); Sijtsma (n 10).

5.6 Integrated interpretation

UTAUT2 highlights anticipated usefulness and support, Trust Theory concerns reliance under uncertainty, and digital governance directs attention to accountability and rights.[23] The study does not validate a model connecting them. It offers a focused distinction between including information about rights, knowing or exercising a right, and receiving useful agricultural advice. A future study can measure these elements independently in a defined user population.

6. Theoretical and Practical Implications

The following implications are prospective recommendations grounded in the item-level findings and relevant literature. The survey does not establish that an intervention improves legal empowerment or agricultural outcomes.

6.1 Theoretical implications

First, rights-information inclusion should be distinguished from legal awareness. A respondent can favour inclusion without being able to identify or apply a right. A future scale should define the legal domain and assess comprehension rather than relying on agreement that information is desirable. Second, usefulness, provider responsibility, data transparency and human help should be measured as separate concepts before testing whether they form any common construct.[24]

Third, the full UTAUT2 framework requires measures of its underlying constructs; the current instrument does not justify claims that its paths are supported. Trust and governance can be integrated into a later model if their content and measurement are defined and the study design supports the intended inference.

6.2 Practical and policy implications

Service providers could identify the organisation responsible for advice, present sources and uncertainty, and explain relevant data practices in language users can understand. Rights-related information should be linked to a defined issue and authoritative sources, with the applicable legal context and date made clear. A functioning route to human assistance or complaint should be tested with the intended users rather than assumed from an interface.

Agricultural extension bodies and technology providers can evaluate accuracy for local crops and conditions, accessibility across devices and languages, and whether users reach an appropriate person after a referral. Studies should include people with different connectivity, literacy, disabilities and agricultural circumstances. A provider's legal obligations must be assessed against the actual service and applicable rules.[25]

7. Conclusion, Limitations and Future Research

Of 385 recorded respondents, 87.8% endorsed including legal-rights information in responsible digital agricultural services, 85.7% endorsed knowing who is responsible for important AI advice, 84.4% endorsed communication of uncertainty and 64.2% endorsed human assistance when advice is inadequate. Rights-information endorsement exceeded endorsement of the usefulness statement by 24.4 percentage points; 215 respondents endorsed both. These are responses to different statements and do not establish the relative effectiveness of service features or an effect on legal awareness.

The study is limited by cross-sectional self-report, an undocumented sampling and fieldwork process, a mixed law-oriented sample,

[23] Venkatesh, Thong and Xu (n 7); Mayer, Davis and Schoorman (n 5); Eastwood and others (n 8).
[24] Boateng and others (n 10).
[25] Bhattarai and others (n 1); Eastwood and others (n 8).

no identified farmer or agricultural-AI-user variable, and no direct test of legal knowledge. The researcher identified the numerical records as real, while the Codebook labels the identifier and contextual-comment fields synthetic; their preparation should be documented. No causal or farmer-population claim follows from the analysis.

Future research should recruit and identify agricultural users and document fieldwork dates, eligibility and recruitment. It should define specific legal scenarios, measure baseline and follow-up understanding, and evaluate whether a user can locate and use a relevant remedy. A service study could vary provider identity, uncertainty disclosure, data information and human referral, then measure comprehension, referral completion, accuracy and practical outcomes. Interviews and accessible user testing would help reveal barriers that general agreement items cannot capture.

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-0020260908-20. 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

Sumtahin Pushpita: 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 survey statements so that each estimate can be interpreted against its exact wording.

Table A1. Exact wording of analytical items

Code	Questionnaire statement
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.
AAR4	Users should have ways to report harmful or inaccurate recommendations.
ADG2	I would use AI agricultural services more confidently if data-use practices were transparent.
AIL1	I understand that generative AI can produce plausible but inaccurate information.

Source: Group 16 Codebook. Answers range from strongly disagree to strongly agree.

Items are analysed separately and do not establish a single validated latent construct.

Table of legislation

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