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The Impact of AI Based Agricultural Advisory Services on Farmers Crop Management Decision Making in Bangladesh: The Mediating Role of Information Quality

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ABSTRACT

Farmers have alternative sources of crop management advice through artificial intelligence based agricultural advisory services. Their contribution will be determined by the availability and personalized advice that contains information that farmers would consider useful in assessing management options. This paper will look at AI advisory accessibility, AI advisory personalization, information quality and quality of crop management decisions among 430 users of agricultural advisory in Bangladesh. A reflective survey was created to measure four reflective constructs with the help of a questionnaire composed of 21 indicators. The measurement quality, direct relationships, indirect relationships, explanatory performance and predictive performance were measured using the partial least squares structural equation modelling. There was a positive relationship between accessibility and personalization and information quality with standardized coefficients of 0.4508 and 0.3880 respectively. Decision quality was directly related to information quality at the highest level of 0.5424. Smaller positive direct relationships of decision quality were also observed with accessibility and personalization. Information quality as the indirect coefficients were 0.2445 and 0.2104, which implies complementary partial mediation. The model was able to explain 42.19 percent of the variance of information quality and 49.55 percent of the variance of decision quality. All endogenous indicators were reported to have positive predictive relevance. Results place information quality at the heart of interconnection between advisory service design and perceived quality of decisions. The use of convenient access, farm specific recommendations and clear standards of information should be integrated to agricultural advisory development.

INTRODUCTION

Crop management involves farmers making decisions that are related during a growing season. There are various information requirements in crop selection, time of planting, irrigation, fertilizers, and pests. What may be the right decision at one point, may prove to be an inappropriate decision as the crop conditions change (Thilakarathne *et al.*, 2022). Agricultural advice is therefore important when it assists farmers to identify a problem, compare how responses can be done and choose an action at the right time. The usefulness of an advisory service lies in the interaction between information provided by the advisory service and the situation in which the decision is made.

Agricultural advisory services using artificial intelligence offer advice via applications, chatbots, automated diagnostic systems and intelligent recommendation tools (Chepken, 2022). These services are able to enable interaction where a farmer explains a problem and is given a response based on the description. They have an agricultural relevance based on the ability to match the available information with a specific crop management question. The fact that there is a smart interface does not create the utility of the advice derived (Weckesser *et al.*, 2022). The information should also be readable, detailed enough, applicable and consistent to the decision under consideration.

Effective advisory use requires accessibility, as a basic requirement. A farmer should have access to advice in case of a crop management issue. This process can be affected by gadgets, communication, time demands, and the amount of effort required to orient in a service (V.Vignesh *et al.*, 2022). A system that is otherwise informative might not help much in practice when it is not convenient to access it. On the other hand, easy availability can assist farmers to go back to the guidance and clarify. Accessibility, then, deals with the terms under which information is made available to be taken into consideration, and not necessarily as to whether there is a digital service or not.

Personalization relates to the alignment of advice and the properties of a farm. Farmers do not grow all types of crops, experience varying growth cycles and experience varying management issues (Druva, 2023). Suggestions based on these conditions can offer a better foundation upon which alternatives can be considered. Accessibility can thus be differentiated with personalization. The concept of accessibility deals with the struggle to access advice. Personalization is about whether that advice is in reaction to the situation of the farmer (Romero-Gainza & Stewart, 2023). Both the service attributes can affect the quality of decisions but their effect can be mediated

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by the perceived quality of the information received.

The focus of explanatory mechanism is the information quality of this study. The farmers will have to assess the accuracy, clarity, detailedness, relevance, up-to-dateness, and consistency of the advisory content (N. & Choudhary, 2022). These judgements may impact on information being added to a management decision. The availability of services can help to obtain valuable information, whereas personalized services can help enhance its contextual applicability. Decisions can then be informed by the quality of information via better problem interpretation and the ability to make decisions based on management options that are more informed (Megeto *et al.*, 2020). This sequence links the attributes of services with the realism of thinking in crop management.

This paper explores these associations among users of agricultural advisory services in Bangladesh. The analysis divides the AI advisory accessibility and AI advisory personalization as two forerunners of the quality of information and quality of decision of crop management. The quality of information is defined as a mediator (Sarkar *et al.*, 2022). This framework allows evaluating the extent to which the service attributes have direct connections to decision quality when the information pathway is taken into account. It also determines whether the indirect relationships explain a significant part of the overall associations that are captured by the model.

The analysis is based on three goals. The initial one is to test the correlations of accessibility and personalization with information quality (Oliveira & Silva, 2023). The second one is to determine the direct relationships between accessibility, personalization, and information quality on the quality of decision-making in crop management. The third is to test the mediating role of information quality between the two service attributes relationships (Chergui & Kechadi, 2022). The combination of these objectives will answer the question of the relationship between advisory design, perceived informational performance and perceived decision quality in one analytical framework. The research adds a differentiated story of the agricultural advisory performance. It does not consider all aspects of AI facilitated advice as a single measure of service. It, instead, determines the access conditions and contextual adaptation independently and analyzes their connections based on information quality (Fabregas *et al.*, 2023). The evidence generated is pertinent to service developers, agricultural extension organizations, and institutions that provide digital advisory delivery (T. Chen *et al.*, 2023). The empirical results refer to the experiences and subjective quality of the decisions that the farmers report, and the interpretation of the results is focused on the relationships, which are estimated in the cross-sectional model.

LITERATURE REVIEW

Agricultural Advisory Services and Decision Quality

Decision making can be facilitated by agricultural advisory services, which coordinate information to a manageable problem. Before taking any action, farmers have to consider a variety of potential reactions (Tsoumas *et al.*, 2023). The value of advice is in part to lessen the confusion regarding these alternatives and help clear up the suitability. The quality of decisions thus deals with the process of determining options, estimation of consequences, choice of suitable practices and selection of appropriate timing (Cawley *et al.*, 2023). Confidence of the applicability of management decisions is also a part of this study. These dimensions are an account of perceived decision performance in the last relevation growing season.

The difference in the qualities of advice and decision is analytically significant. An information input is a recommendation, and a management decision is an information input that is combined with the conditions on the farm and practical limitations (Prasad *et al.*, 2020). This can be facilitated by a friendly advisory service, which does not dictate what the farmer should do. In line with this, the model analyses a relationship between the features of services and perceived decision quality. It is not the equivalent of a positive evaluation of advice and changes in production independently measured (Mahibha & Balasubramanian, 2023). This differentiation maintains the conceptual interpretation in line with the questionnaire focus of the management judgements of the farmers.

Accessibility and Information Quality

AI advisory accessibility is the quality of access to advice. Its indicators include the availability when required, convenience, the absence of unwarranted difficulty, the availability of devices and communication channels, and controllable time and effort (Veettil *et al.*, 2021). These aspects detail how an experience of an advisory content transpires in a farmer. With increased accessibility, farmers can have increased access to information at the appropriate times and re-evaluate guidance as their questions evolve (Gangolla Priya *et al.*, 2022). This connection allows anticipating that accessibility is going to be linked to the perceived information quality in a positive way.

The significance of interaction is also observed in the proposed relationship. Agricultural inquiries can need clarification prior to response becoming valuable (Gupta *et al.*, 2023). What a farmer can revisit a service with minimal effort, can be in a better position to get enough detail or clarify an indeterminate piece of advice. Accessibility can hence be a part of the informational experience that exists after the initial contact. The model does not presuppose the case where convenient access is the only assurance of the correct content (Viloria *et al.*, 2021). It suggests that conditions of access are more favourable, the more favourable the assessment of the received information is.

H1: The perceived quality of information in the AI based agricultural advisory services is positively correlated with AI advisory accessibility.

Personalization and Information Quality

AI advisory personalization is the degree to which the recommendations cover particular needs of farming (Yogita Kharde *et al.*, 2022). Its measurement incorporates the type of crop, stage of crop development, specific management issues, reports about the farm status, and personal needs. The following dimensions differentiate between contextual advice and advice that is independent of the situation under consideration (Renushe *et al.*, 2023). Farmers can also interpret and apply the content in such a service more easily when it reacts to the pertinent information about the farm. Personalization will, in turn, be connected with an increased perceived information quality.

The relationship between a recommendation and the question that led to the recommendation may be enhanced by being personalized. Suggestions on irrigation, such as, are more valuable taking into account the crop and its stage (Naresh *et al.*, 2020). Nutrient management and reaction to crop health issues can also be viewed according to the same principle. Contextual adaptation can also be used to arrange information around a short-term interest of a farmer. Nevertheless, personalization and the information quality are separate constructs (Thilakarathne *et al.*, 2022). A response may be specific to a given farm, yet needs to be assessed in terms of clarity, currency, consistency and perceived accuracy.

H2 states that AI advisory personalization has a positive association with the perceived information quality of AI based agricultural advisory services.

Information Quality and Crop Management Decisions

Information quality deals with the features that render advice appropriate to the consideration. Accuracy is concerned with the perception of the content as correct. Clarity is whether it has a meaning to be comprehended (Weckesser *et al.*, 2022). Detailed will assist in making comparisons among alternatives and relevancy will help relate the content with the problem of the farmer. Currency has the issue to do with its suitability to the current needs. Consistency discusses the topic of similar conditions being given coherent guidance (V.Vignesh *et al.*, 2022). The combination of these characteristics can offer an informational basis to the management that would be more reliable.

Good information can be used in various phases of decision making. Explanations can be made clear to identify the management options (Megeto *et al.*, 2020). Assessment may be done on the basis of advantages and disadvantages and relevant detail may be given. Timing can be supported by the information available in the present and certainty can be enhanced by consistent advice in the rationale behind the decision (Sarkar *et al.*, 2022). The proposed association thus deals with an overall decision process and not with a particular action. It is assumed that farmers who rate advisory information more positively will record higher-ranking to make appropriate, timely, and thoughtful crop management decisions (Oliveira & Silva, 2023).

H3: The quality of information is positively related to the quality of farmers in terms of their crop management decisions.

Direct Relationships Between Service Attributes and Decision Quality

Even considering information quality, accessibility may still have a direct correlation with quality of decisions. Availability of advice at time when a decision has to be made can be convenient (Chergui & Kechadi, 2022). The cost of interaction can also be manageable and in such a situation, farmers can consult a service and then make a decision. These practical conditions apply to the making of decisions in time and reflecting on the options (Fabregas *et al.*, 2023). The direct route is the association of remaining accessibility vis-a-vis decision quality following the given information quality route.

Personalization can also have a direct relationship with quality of decisions. Appropriate recommendations associated with a crop of a farmer, the reported conditions, and the immediate problem can facilitate the available options to relate to farm practice (T. Chen *et al.*, 2023). Applicability of these responses can be helped by such adaptation to help in choosing the appropriate responses to use and in assessing their suitability. The direct association enables such an association to be approximated along with the indirect association using information quality (Tsoumas *et al.*, 2023). It thus does not presume that all the gains that are supposed to come with personalization should be fully embodied by the overall consideration of the information quality by a farmer.

H4 states that AI advisory accessibility has a positive association with farmers' crop management decision quality. H5 states that AI advisory personalization has a positive association with farmers' crop management decision quality.

The Mediating Role of Information Quality

The mediation model suggests that access is linked to quality of decisions partially with the information quality. The receipt and clarification of advice can be facilitated by ease of access (Cawley *et al.*, 2023). More positive judgements of such advice can then be linked to improved perceived management decisions. The product of the accessibility to the quality of information path and the information quality to decision quality path shows the indirect relationship that was used. The presence of a positive indirect coefficient would facilitate the suggested informational mechanism in the estimated model (Prasad *et al.*, 2020).

Personalization is postulated to take place in a parallel manner. Information quality assessments might be more robust in decision advice that is tailored to the nature of crops and farm environment (Viloria *et al.*, 2021). Such assessments can, in its turn, be linked with more thoughtful and appropriate management decisions. Incorporating the two mediating pathways allows comparing their contributions without lumping

accessibility and personalization together into a single construct (Gangolla Priya *et al.*, 2022). The framework also maintains the two direct paths, which makes the analysis to find out whether mediation is correlated with other positive relationships to decision quality.

H6: The quality of information has a positive mediating effect on the association between advisory accessibility of AI and the quality of crop management decision. H7 is the information quality mediates the relation between the AI advisory personalization and the quality of crop management decisions (Viloria *et al.*, 2021). This corresponds to a total of four constructs, five direct relationships and two specific relationships (indirect). Exogenous constructs are accessibility and personalization (Renushe *et al.*, 2023). The information quality and crop management decision quality are endogenous constructs and information quality is placed between the two service attributes and the eventual outcome.

MATERIALS AND METHODS

Research Design and Analytical Scope

The research design is a quantitative cross-sectional approach to the relationships between agricultural advisory experiences and perceived quality of decisions. The individual farmer who has to make decisions either in crop cultivation or management is the unit of analysis. The sample size is 430 responses that are analyzed. The questionnaire will eligibility criteria which include involvement in crop management during the last 12 months and use of an AI based agricultural advisory service. Measurement statements are the last season of growing which was completed, during which a respondent referred to an identified advisory service. The questionnaire outlines AI on the basis of agricultural advisory services as applications, intelligent chatbots, automated crop diagnosis systems and other AI enabled technologies that offer agricultural prescribing (Adaikkalam Zabihi *et al.*, 2025). This definition helps to distinguish between intelligent advisory interactions and digital information channels in general. When respondents are unsure about the functionality of a named service, screening instructions must verify that service. The interpretative interpretation relates to qualified advisory users and experiences they report. The research design assists in estimating the association and mediation patterns within that group of users.

Questionnaire Structure and Measurement

The tool has information about consent, screening questions, demographic and farming characteristics, and construct measurements. Background questions deal with gender, age, educational level, experience working in farms, land under cultivation, type of crop, where it is grown, type of advisory service, how it is used regularly, purpose of use, and the method of access (Mellenbergh *et al.*, 2003). These characteristics describe the composition of the analytical sample. The consent statement mentions participation as being voluntary and that responses will be used to conduct academic research. It does not involve any personal information about the respondents.

There are 21 statements used to measure four reflective constructs. AI advisory accessibility, AI advisory personalization, information quality, and crop management decision quality have five, five, and five items respectively. There are five-point agreement scales to which all the statements have been applied (strongly disagree to strongly agree). The greater the responses, the more positive the assessment of the construct is. The reflective specification considers the indicators as expressions of the underlying concepts. Measurement assessment thus takes into consideration indicator loadings, internal consistency, convergence and discriminant validity.

The quality of information items includes perceived accuracy, clarity, adequacy of detail, relevance, currency and consistency (Andiappan & Wan, 2020). Decision quality items would deal with the identification of the correct options, having the right time, suitability to the farm conditions, evaluating alternatives and having confidence in the decisions made. These definitions keep the concept of the mediator conceptually separate of the outcome. Information quality is the measure of advisory content and decision quality is the measure of management choices of a respondent. The conceptual model explains accessibility and personalization as the service experience that precurs such evaluations.

Data Screening and Sample Description

Screening measures eligibility, completeness, response range, duplicated profiles and straightlined profiles. The findings show 430 initial responses and 430 eligible

Table 1: Data Screening and Response Quality Assessment

Metric	Result
Initial responses	430
Eligible responses	430
Excluded at screening	0
Missing measurement values	0
Invalid Likert responses	0
Duplicate profiles flagged	0
Straightlined profiles flagged	0
Final sample size	430
Measurement indicators	21
Dataset status	430 survey responses

responses and no exclusions. None of the values of missing measurement or invalid Likert responses are mentioned. No flagged cases are recorded by duplicate and straightlined profile checks either (Mimansha Patel & Nitin Patel, 2019). The entire sample of 21 measurements indicators is thus included in the final analysis sample. Table 1 shows the results of the screening and provides the response base, which will be used in the further analysis.

Frequencies and percentages are used to summarize the sample profile. Demographic codes are understood based on the questionnaire types. Characteristics of respondents are gender, age, education, experience in farming, and landholding. Farming and advisory practices include crop type, location, advisory service type, frequency, purpose, and access mode. These overviews offer a backdrop in understanding the structural relationships (Y. Chen, 2023). They are not explanatory variables in the given model, and it revolves around the four major constructs and their hypothesized relationships.

Statistical Assessment

The reflective measurement model and the structural relationships are assessed with the help of partial least squares structural equation modelling. Measurement assessment involves outer loadings, Cronbachs alpha, rho A, composite reliability and average variance extracted. The heterotrait monotrait ratio and bootstrap intervals are used to calculate discriminant validity (Adaikkalam Zabihi *et al.*, 2025). Full collinearity and inner variance inflation factors are used to analyze the situation of collinearity. Such procedures determine the interpretability of the constructs as independent entities and whether the overlap of the predictors poses a problem in estimating the structure.

The structural analysis looks at standardized coefficients, known standard errors, test statistic, p value, and bootstrap interval. The mediation hypotheses are tested using specific indirect effects and direct and indirect relationships are summed using total effects. R squared and adjusted R squared are used to summarize explanatory performance. Effect sizes determine the effect of individual predictors. Predictive assessment involves the use of reported tenfold procedure, indicator level predictive relevance and prediction errors comparisons with a linear model benchmark. Descriptive correlations and structural coefficients are understood based on their analytical uses.

RESULTS AND DISCUSSION

Respondent Characteristics

The sample is comprised of 70.47 percent male respondents and 28.14 percent female respondents. The highest age group is 35 to 44 years, which constitute

Table 2: Demographic Characteristics of Respondents

Characteristic	Category	Frequency	Percentage
Gender	Male	303	70.47
Gender	Female	121	28.14
Gender	Other or self described	2	0.47
Gender	Prefer not to disclose	4	0.93
Age	Below 25 years	45	10.47
Age	25–34 years	112	26.05
Age	35–44 years	125	29.07
Age	45–54 years	91	21.16
Age	55 years and above	57	13.26
Education	No formal education	25	5.81
Education	Primary education	119	27.67
Education	Secondary education	156	36.28
Education	Higher secondary education	86	20.00
Education	Undergraduate or above	44	10.23
Experience	Less than 5 years	106	24.65
Experience	5–10 years	113	26.28
Experience	11–15 years	73	16.98
Experience	16–20 years	69	16.05
Experience	More than 20 years	69	16.05
Cultivated land	Below 50 decimals	117	27.21
Cultivated land	50–99 decimals	129	30.00
Cultivated land	100–199 decimals	101	23.49
Cultivated land	200 decimals or above	70	16.28
Cultivated land	Prefer not to disclose	13	3.02

29.07 percent, and 25 to 34 years, which constitute 26.05 percent. The most common type of education is secondary education with 36.28 percent and then primary education with 27.67 percent. These distributions are characterized by a sample that has diverse educational levels and high numbers in the focal age groups.

Experience in farming is too spread out in a number of categories. The respondents aged five to ten years constitute 26.28 and those having less than five years constitute 24.65 percent. The biggest land area 30.00 percent is the cultivated land of 50 to 99 decimals. Another 27.21 percent indicate less than 50 decimals. These attributes apply to the real-life context of how to interpret advisory access since the sample would consist of farmers of various experiences and land under cultivation.

The majority of the respondents (45.58 percent) use rice as the major crop when compared to vegetables (28.60 percent). Responses cover 12 districts. The highest percentage is 14.19 in Mymensingh, 11.16 in Bogura, and 10.47 in Jamalpur. There is a variability in farming location and focus on crops thereby in the sample. These distributions help put the context to the advisory experiences under assessment and the structural analysis estimated the proposed relationships on the combination of the sample.

The most commonly cited type of advisory service is agricultural mobile apps at 27.21 percent followed by chatbots or virtual assistants at 25.81 percent. The use once or twice monthly (27.44 percent) and use approximately weekly (28.37 percent) contribute approximately 28.37 percent and 27.44 percent, respectively. The most common one is pest and disease management at 33.95 percent. independent access via computer or smartphone is 48.84 per cent. The other types of access imply that family members, extension officers, and service providers are also engaged in the advisory use.

Table 3: Farming Characteristics and AI Advisory Service Usage

Characteristic	Category	Frequency	Percentage
Primary crop	Rice	196	45.58
Primary crop	Wheat	29	6.74
Primary crop	Maize	38	8.84
Primary crop	Vegetables	123	28.60
Primary crop	Fruits	30	6.98
Primary crop	Other	14	3.26
District	Barishal	25	5.81
District	Bogura	48	11.16
District	Cumilla	28	6.51
District	Dinajpur	31	7.21
District	Jamalpur	45	10.47
District	Jashore	32	7.44
District	Khulna	36	8.37
District	Mymensingh	61	14.19
District	Natore	22	5.12
District	Rajshahi	31	7.21
District	Rangpur	29	6.74
District	Sherpur	42	9.77
Service type	Agricultural mobile application	117	27.21
Service type	Chatbot or virtual assistant	111	25.81
Service type	Crop disease identification	79	18.37
Service type	Crop management recommendations	76	17.67
Service type	AI assisted extension	47	10.93
Frequency	Less than monthly	56	13.02
Frequency	Once or twice monthly	118	27.44
Frequency	Approximately weekly	122	28.37
Frequency	Several times weekly	108	25.12
Frequency	Daily or almost daily	26	6.05
Main purpose	Pest and disease management	146	33.95
Main purpose	Fertilizer and nutrients	91	21.16

Main purpose	Irrigation	62	14.42
Main purpose	Crop selection and planting	51	11.86
Main purpose	Weather related decisions	65	15.12
Main purpose	Other	15	3.49
Access mode	Independent digital access	210	48.84
Access mode	Family assistance	69	16.05
Access mode	Extension officers	76	17.67
Access mode	Service providers	53	12.33
Access mode	Other	22	5.12

Item and Construct Descriptive Statistics

The average of the measurement items is between 2.8302 and 3.1767. The mean of accessibility item AAA1 is the highest, whereas personalization item AAP3 is the lowest. The standard deviations are 1.1207 to 1.2170, which implies variation of the responses around the core scale categories. All measurement items run through the whole range of response; one to five. The descriptive trend thus indicates varied considerations as opposed to homogenous consensus among the advisory experience's measures.

Table 4: Descriptive Statistics of Measurement Items

Construct	Indicator	Mean	SD	Skewness	Excess kurtosis
AAA	AAA1	3.1767	1.1512	-0.1374	-0.7354
AAA	AAA2	2.9535	1.1935	0.0238	-0.8912
AAA	AAA3	3.0512	1.1332	0.0439	-0.7927
AAA	AAA4	3.1581	1.1858	-0.0390	-0.8862
AAA	AAA5	3.1302	1.1833	-0.1094	-0.8560
AAP	AAP1	2.9884	1.1271	0.0815	-0.7833
AAP	AAP2	3.1070	1.1558	0.0537	-0.7907
AAP	AAP3	2.8302	1.1370	0.0787	-0.7012
AAP	AAP4	2.8535	1.1765	0.1481	-0.8499
AAP	AAP5	2.8907	1.1586	0.1416	-0.7841
IQ	IQ1	3.0860	1.2059	-0.1095	-0.9142
IQ	IQ2	3.0209	1.1207	0.0384	-0.6426
IQ	IQ3	3.0326	1.2133	-0.0858	-0.9036
IQ	IQ4	3.0907	1.2132	-0.0015	-0.9508
IQ	IQ5	3.0721	1.1575	0.0399	-0.8140
IQ	IQ6	3.1163	1.2082	-0.0332	-0.8760
CMDQ	CMDQ1	3.0372	1.2170	-0.0867	-0.8862
CMDQ	CMDQ2	3.1349	1.1508	-0.1178	-0.7897
CMDQ	CMDQ3	2.9651	1.1552	-0.0046	-0.7113
CMDQ	CMDQ4	2.9721	1.1360	-0.0504	-0.8007
CMDQ	CMDQ5	2.9814	1.1342	0.0941	-0.7250

The means of accessibility at the construct level are 3.0940, information quality is 3.0698 and decision quality is 3.0181. The mean of personalization is lowest at 2.9340. These values reveal that there is a mean score of agreement that lies at the mid mark of the agreement scale. In turn, the positive structural relationships cannot be viewed as the indication of the homogeneous high levels of satisfaction. They detail the relationship between differences in the constructs with each other among the respondents.

The largest descriptive correlation is between the quality of information and the quality of decisions at 0.6213. There is a correlation of 0.4770 between accessibility and information quality, and a correlation of 0.4282 between personalization and information quality. The weaker linkage is 0.1741 between accessibility and personalization. This trend can be related to the interpretation of the two advisory characteristics as related and different characteristics of service (Thilakarathne *et al.*, 2022). The descriptive correlations provoke the direction of the observed relations prior to the measurement and structural tests are taken into account.

Table 5: Construct Descriptive Statistics and Correlations

Construct	Mean	SD	AAA	AAP	IQ	CMDQ
AAA	3.0940	0.9825	1.0000	0.1741	0.4770	0.4061
AAP	2.9340	0.9537	0.1741	1.0000	0.4282	0.3865
IQ	3.0698	0.9870	0.4770	0.4282	1.0000	0.6213
CMDQ	3.0181	0.9826	0.4061	0.3865	0.6213	1.0000

Indicator Reliability and Convergent Validity

Outer loadings range from 0.6871 to 0.8651 for accessibility, 0.7202 to 0.8330 for personalization, 0.7434 to 0.8348 for information quality, and 0.7456 to 0.8477 for decision quality. The lowest loading of accessibility item AAA2 is 0.6871 and it still exists in the reported specification. The results of its interpretation are discussed in connection with the construct level reliability and convergence results. The other indicators have higher loadings and this can be said to underpin their contribution to the respective reflective constructs.

Table 6: Indicator Reliability Assessment

Construct	Indicator	Loading	Squared loading
AAA	AAA1	0.8651	0.7484
AAA	AAA2	0.6871	0.4722
AAA	AAA3	0.7604	0.5782
AAA	AAA4	0.7947	0.6315
AAA	AAA5	0.8524	0.7265
AAP	AAP1	0.7202	0.5187
AAP	AAP2	0.7737	0.5986
AAP	AAP3	0.8076	0.6523
AAP	AAP4	0.8330	0.6939
AAP	AAP5	0.7596	0.5770
IQ	IQ1	0.8348	0.6970
IQ	IQ2	0.8285	0.6864
IQ	IQ3	0.7475	0.5588
IQ	IQ4	0.7434	0.5526
IQ	IQ5	0.8069	0.6511
IQ	IQ6	0.8036	0.6458
CMDQ	CMDQ1	0.8477	0.7186
CMDQ	CMDQ2	0.8450	0.7140
CMDQ	CMDQ3	0.8179	0.6690
CMDQ	CMDQ4	0.7456	0.5560
CMDQ	CMDQ5	0.7703	0.5933

The alpha of Cronbach is between 0.8857 and 0.9111, and the composite reliability is between 0.8856 and 0.9114. The rho_A values range from 0.8874 to 0.9126. Accessibility, personalization, information quality and decision quality have an average variance extracted of 0.6313, 0.6081, 0.6319 and 0.6502, respectively. All the constructs thus explain over 50 percent of its indicator variance in reported assessment. Collectively, the results justify internal consistency and convergent validity of the retained specification of measurement.

Table 7: Internal Consistency Reliability and Convergent Validity

Construct	Alpha	rho A	CR	AVE
AAA	0.8958	0.8995	0.8948	0.6313
AAP	0.8857	0.8874	0.8856	0.6081
IQ	0.9111	0.9126	0.9114	0.6319
CMDQ	0.9020	0.9045	0.9026	0.6502

Discriminant Validity and Collinearity

The heterotrait monotrait ratios are between 0.1937 to 0.6839. The greatest value lies between the information quality and decision quality, which is the relative strength of the two variables but still lower than the reported discriminant validity value. The lowest ratio, at 0.1937 is accessibility and personalization. These findings endorse the difference between access conditions, contextual adaptation, information evaluation and decision evaluation. The constructs may thus be viewed as independent units of the proposed advisory model.

Table 8: Discriminant Validity Assessment Using HTMT

Construct	AAA	AAP	IQ	CMDQ
AAA	—	0.1937	0.5254	0.4477
AAP	0.1937	—	0.4752	0.4310
IQ	0.5254	0.4752	—	0.6839
CMDQ	0.4477	0.4310	0.6839	—

The bootstrap intervals provide further support for this distinction. Their upper limits include 0.2980 which is accessibility and personalization and 0.7417 which is the information quality and decision quality. No one of the reported intervals contains one. The confidence interval of the strongest construct pair goes between 0.6237 and 0.7417. The evidence shows that overall informational evaluation and decision evaluation are closely related; these evaluations do not fall in one construct of the reported assessment.

Table 9: HTMT Bootstrapped Confidence Intervals

Construct pair	HTMT	CI Lower	CI Upper
AAA - AAP	0.1937	0.1004	0.2980
AAA - IQ	0.5254	0.4442	0.6009
AAA - CMDQ	0.4477	0.3601	0.5325
AAP - IQ	0.4752	0.3974	0.5544
AAP - CMDQ	0.4310	0.3402	0.5063
IQ - CMDQ	0.6839	0.6237	0.7417

Full collinearity variance inflation factors are between 1.2667 and 1.9458. These are lower than the diagnostic reference 3.3 that is contained in the workbook. They show no high levels of full collinearity in that check. The finding is considered a diagnostic finding and not a clear removal of all the possible influence on the response methods. It should only help in interpretation of the model in conjunction with the other measurement assessments, and not to determine that all possible sources of shared response variation have been eliminated.

Table 10: Common Method Bias Diagnostic Assessment

Construct	Full VIF
AAA	1.3342
AAP	1.2667
IQ	1.9458
CMDQ	1.7264

The factors of inflation within the inner variance are between 1.0313 and 1.5393. Both accessibility and personalization are predicted with a value of 1.0313 in determining the quality of information. The values of these in terms of quality of decisions are 1.2963 accessibility, 1.2263 personalization and 1.5393 information quality. These results reveal that the predictor collinearity is not observed to be high in either of the

Table 11: Structural Model Collinearity Assessment

Outcome	Predictor	Inner VIF
IQ	AAA	1.0313
IQ	AAP	1.0313
CMDQ	AAA	1.2963
CMDQ	AAP	1.2263
CMDQ	IQ	1.5393

endogenous equations. The instant coefficients can thus be tested without the indication of a high level of overlap amongst the outlined predictors.

Explanatory Performance and Effect Sizes

The model accounts 42.19 percent of the variation in information quality and 49.55 percent in the quality of crop management decision. Adjusted values have been 0.4192 and 0.4920 respectively. The close similarities between the raw and the adjusted statistics imply that explanatory estimates are similar after the number of predictors are taken into consideration. The findings provide significant explanatory performance in the sample under analysis (Chepken, 2022). They deal with variation in the measured constructs and must not be interpreted as percentages of improvement of agricultural production.

Table 12: Coefficient of Determination

Construct	R^2	Adjusted R^2
IQ	0.4219	0.4192
CMDQ	0.4955	0.4920

The accessibility effect size in the information quality equation is 0.3382 and that of personalization is 0.2504. The effect size of information quality in decision quality equation is 0.3370. These three relationships are classified as medium in the workbook. The positive effects, in turn, of accessibility and personalization on the quality of decisions are smaller, and they are 0.0267 and 0.0325. The trend puts the major structural contribution on the course of information and leaves smaller direct contributions of the two service attributes.

Table 13: Effect Size Assessment

Hypothesis	Path	f^2	Size
H1	AAA → IQ	0.3382	Medium
H2	AAP → IQ	0.2504	Medium
H3	IQ → CMDQ	0.3370	Medium
H4	AAA → CMDQ	0.0267	Small
H5	AAP → CMDQ	0.0325	Small

Direct Relationships and Hypothesis Testing

The accessibility is positively correlated with the quality of information, the standardized coefficient between them is 0.4508 with a standard error of 0.0394 and the p value of 0.001. Its range of bootstrapping is between 0.3724 and 0.5273. H1 can thus be supported. There is also a positive relationship between personalization and information quality with a coefficient of 0.3880 and standard error of 0.0413 and the reported p value of 0.001. The range of its interval lies between 0.3094 and 0.4686, which is in favor of H2.

There is the most direct relationship between information quality and decision quality whose coefficient equals 0.5424 and the standard error is 0.0528. The reported p value is 0.001, and the interval extends from 0.4399 to 0.6432. H3 is supported. This outcome indicates that increased perceived information quality is related to increased perceived decision quality in a structural equation where accessibility and personalization are both added. The coefficient goes along with the central location assigned to quality of information in the conceptual model.

Accessibility has a direct positive correlation with the quality of the decision at 0.1361, the p value of 0.009 and a range of 0.0360 to 0.2383. Personalization has a direct coefficient of 0.1468 and its p value is 0.002 with an interval of 0.0518-0.2315. H4 and H5 are justified. The direct coefficients are both negative than the information quality coefficient meaning the greatest conditional relationship with decision quality is of the mediator.

Table 14: Direct Effects and Hypothesis Testing

Hypothesis	Relationship	β	t	p	Bootstrap interval
H1	AAA → IQ	0.4508	11.4356	0.001	0.3724 to 0.5273
H2	AAP → IQ	0.3880	9.3947	0.001	0.3094 to 0.4686
H3	IQ → CMDQ	0.5424	10.2734	0.001	0.4399 to 0.6432
H4	AAA → CMDQ	0.1361	2.6517	0.009	0.0360 to 0.2383
H5	AAP → CMDQ	0.1468	3.2272	0.002	0.0518 to 0.2315

Mediation and Total Relationships

The information quality relationship with indirect accessibility is 0.2445, standard error of 0.0321 and reported p value of 0.001. Its interval extends from 0.1841 to 0.3115. The standard error is 0.0319, the reported p value is 0.001 and the indirect personalization relationship

is 0.2104. Its interval extends from 0.1544 to 0.2801. The two intervals are positive and in favour of H6 and H7. The results agree with the fact that information quality operates as a positive mediator in the two associations.

Table 15: Mediation Analysis: Specific Indirect Effects

Hypothesis	Indirect path	β	t	p	Bootstrap interval
H6	AAA → IQ → CMDQ	0.2445	7.6227	0.001	0.1841 to 0.3115
H7	AAP → IQ → CMDQ	0.2104	6.6035	0.001	0.1544 to 0.2801

The positive indirect relationships are complementary with positive direct relationships. This combination implies the existence of complementary partial mediation in the described model. Accessibility is also associated with the decision quality with a total of 0.3806, and personalization has a total of 0.3572. Division of every indirect coefficient with its own total coefficient results in the following values: 64.24 percent in terms of accessibility and 58.90 percent in terms of personalization. These descriptive proportions indicate how prominent are the mediated components; these proportions are not causal proportions of observed agricultural improvement.

Table 16: Total Effects Assessment

Relationship	β	t	p	Bootstrap interval
AAA → IQ	0.4508	11.4356	0.001	0.3724 to 0.5273
AAP → IQ	0.3880	9.3947	0.001	0.3094 to 0.4686
IQ → CMDQ	0.5424	10.2734	0.001	0.4399 to 0.6432
AAA → CMDQ	0.3806	8.6934	0.001	0.2984 to 0.4646
AAP → CMDQ	0.3572	8.4549	0.001	0.2733 to 0.4379

Predictive Assessment and Consolidated Findings

The tenfold predictive assessment shows positive values of Q squared predict of all 11 endogenous indicators. The values of the indicators of information quality lie between 0.2102 and 0.2730, and the values of the indicators of decision quality are between 0.2468 and 0.3283. The errors of the PLS prediction are less than the errors of the linear model prediction of all indicators in root mean squared error and mean absolute error. The acquired findings thus serve as predictive utility as compared to the benchmark incorporated in this study.

Table 17: Out-of-Sample Predictive Assessment

Indicator	Construct	Q^2 predict	PLS RMSE	LM RMSE	PLS MAE	LM MAE
IQ1	IQ	0.2730	1.0290	1.0432	0.8474	0.8546
IQ2	IQ	0.2477	0.9716	0.9872	0.7901	0.8015
IQ3	IQ	0.2134	1.0762	1.0907	0.8797	0.8904
IQ4	IQ	0.2102	1.0778	1.0917	0.8818	0.8867
IQ5	IQ	0.2255	1.0181	1.0294	0.8195	0.8261
IQ6	IQ	0.2379	1.0549	1.0741	0.8669	0.8836
CMDQ1	CMDQ	0.3264	0.9981	1.0213	0.8277	0.8477
CMDQ2	CMDQ	0.3283	0.9436	0.9599	0.7697	0.7777
CMDQ3	CMDQ	0.2996	0.9662	1.0013	0.7858	0.8188
CMDQ4	CMDQ	0.2468	0.9857	1.0066	0.8129	0.8270
CMDQ5	CMDQ	0.2629	0.9731	0.9950	0.7968	0.8121

The enhancements in the predictions are uniform throughout the indicators, but the differences in numbers when compared to the linear benchmark are small. Root mean squared error enhancements lie between 0.0113 and 0.0192 in regard to information quality. Their decision quality varies between 0.0163 and 0.0351. This trend further complements the explanatory evaluation by demonstrating that the topicality of the model is not limited to the significance of structural coefficients. All the seven hypothesis decisions are summarized in Table 18 that validates that all the proposed relationships have been confirmed in the presented analysis.

Table 18: Summary of Hypothesis Testing Results

Hypothesis	Relationship	β	p	Bootstrap interval	Decision
H1	AAA → IQ	0.4508	0.001	0.3724 to 0.5273	Supported
H2	AAP → IQ	0.3880	0.001	0.3094 to 0.4686	Supported
H3	IQ → CMDQ	0.5424	0.001	0.4399 to 0.6432	Supported
H4	AAA → CMDQ	0.1361	0.009	0.0360 to 0.2383	Supported
H5	AAP → CMDQ	0.1468	0.002	0.0518 to 0.2315	Supported
H6	AAA → IQ → CMDQ	0.2445	0.001	0.1841 to 0.3115	Supported
H7	AAP → IQ → CMDQ	0.2104	0.001	0.1544 to 0.2801	Supported

Discussion

Information Quality as the Central Advisory Mechanism

The key conclusion is that the information quality is at the core of the bond between the nature of advisory services and quality of crop management decisions (Weckesser *et al.*, 2022). The direct coefficient of it is higher than any of the direct service attribute coefficients. It also has a significantly large effect size as compared to the individual effect sizes of accessibility and personalization on the outcome. The result shows that the farmers in their assessment of advisory content have a close relationship with their assessment of management decisions. Service design thus can be made analytically relevant using the information provided to farmers and judged.

This meaning is based on the content of the constructs (Druva, 2023). Quality, unambiguous, topical, thorough, and harmonious advice provides a platform of strength on which to assess options. Issues of quality in decisions involve making appropriate decisions based on the nature of options selected, timeliness of decision, appropriateness of practices to fit the farm conditions, alternative options and whether the decisions made seemed good or not. These two concepts are thus substantively related. Information quality is related to the inputs to be judged whereas the quality of decision relates to the performance of the decision being reported. The results of the discriminant validity confirm the need to keep the two different even though they are closely related.

This account is reinforced by the mediation results. The indirect component represents more than half of all the total service attribute association by presenting the quality of information (N. & Choudhary, 2022). This makes accessibility and personalization important in a significant degree as they are linked with more positive informational judgments. This discovery guides towards the material presented by advisory systems. Enlarging contact possibilities or enriching contextual reference material might not be adequate when the ensuing information is not used to make farmers perceive a management issue and evaluate an appropriate response.

The Contribution of Accessibility

Accessibility is closely related to information quality and has a lesser remaining direct relationship with the quality of the decision. The former connection is in line with the significance of timely and manageable access to guidance (Megeto *et al.*, 2020). The ease with which farmers can access an advisory service might enable them to access pertinent information and seek clarifications. The lesser direct correlation is in line with the practical importance of seeking advice when it comes to making decisions. Both elements fit within the larger stance that the conditions of access determine the utility of agricultural advisory interactions.

This is put into a practical context by the access patterns of the sample. Less than half of the respondents indicate having independent access via a smartphone or computer. Other respondents rely on family members, extension officers or service provider's support. The concept of accessibility must thus be interpreted in multiple paths instead of the direct personal device operation (Sarkar *et al.*, 2022). A system can be made available via a middle man who assists in developing a question or decoding a reply. Service evaluation ought not to overlook the entire path a farmer will go through in order to receive guidance.

The Contribution of Personalization

Both information quality and decision quality have positive correlations with personalization. Its indirect coefficient is larger than the direct one, which proves the fact that the informational pathway is of particular importance. Recommendations that are tailored to crop type, growth stage, presented problems, and farm conditions, can be appraised in a more favourable manner as they align with the question presented by the farmer (Oliveira & Silva, 2023). This fact relationship postulates that personalization is desirable to enhance the practicality of the content. The analytical outcome refers to the responsiveness within the context as opposed to the apparent presence of individual attention.

The construct mean of personalization is also the lowest. The combination here is informative: the attribute has a positive correlation with the outcome, but the respondents do not report the equal experience with personalisation. Development of service can thus prioritize the quality of the contextual inputs and its application in the recommendations (Chergui & Kechadi, 2022). Requesting farmers to provide stage of crop or condition of farm is only worthwhile when the meaning of the response integrates the stage of crop or condition of the farm.

The results justify the measure of personalization based on the relation between the gathered information and the advice given back to the farmer.

Interpreting Explanatory and Predictive Performance

The model explains almost half of the variability in decision quality and a significant percentage of the variability in information quality. These findings confirm the applicability of the chosen constructs to comprehend advisory experiences of farmers. They also state that the result is described by a series of interrelated relationships as opposed to one service attribute. The informational evaluation is enhanced by accessibility and personalization, and the strongest direct relationship with the quality of decision is the one between information quality and the quality of the decision (Chergui & Kechadi, 2022). The explanatory scheme is thus consistent with the suggested structure.

The predictive results are an additive view. The presence of positive indicator level predictive relevance and lower errors than the linear benchmark indicates the usefulness of the model in practical statistics in the assessment reported. The modest numerical improvements call for proportional interpretation (Fabregas *et al.*, 2023). Evidence is much more predictable compared to the given comparison, whereas the substantive contribution is the determination of the information pathway. Explanatory performance, predictive performance, and hypothesis support answer various questions and must be addressed jointly when analyzing the model.

Another implication relates to the difference between the average evaluations and construct-construct relationships. The means are near the scale midline; the structural coefficients are positive and statistically supported. These findings provide response to various questions. The means are used to describe the overall level of experience reported (T. Chen *et al.*, 2023). The coefficients explain the variation of respondents with various evaluations within the model. A service may thus exhibit a significant correlation with the quality of the decision when its average rating is average. This difference justifies focus on enhancing service experiences and maintaining the explanatory power of the relationships established.

The smaller direct coefficients should be carefully interpreted as well. Their statistical evidence suggests that accessibility and personalization maintain relationships with quality of decision with the mediator added. The small value of their effects implies that such left over contributions are relatively small in the given equations (Prasad *et al.*, 2020). Practical priorities must therefore factor in the magnitude of coefficients, effect size as well as the mediation results. It would be appealing to concentrate on just the support of a hypothesis when one should highlight the more significant information channel. The combined analysis provides a more effective ground on which to interpret what aspects of the advisory experience are most likely to be related to the measured outcome.

The framework is also able to structure service monitoring around stages that are interconnected. Access measures characterize the possibility of arriving at the guidance (Veettil *et al.*, 2021). Contextual responsiveness is described as personalization measures. Information measures evaluate the content received. Decision measures review reported management process. Separating these stages enables service evaluation to see where enhancements are required without considering all the positive responses the same outcome.

Practical and Theoretical Implications

The results justify a combined method in designing an advisory in agriculture. Accessibility should be thought of in terms of manageable interaction needs, accessible channels of communication, and assisted access. Services ought to enable farmers to access guidance without being over navigated or duplicating what has been done. Since advisory use takes place in the independent and the intermediary channels, access arrangements must support the farmers that may be those receiving family support or the extension (Gupta *et al.*, 2023). These steps are taken in accordance with the perceived value of access without presupposing the similarity of how all users interact with technology.

Personalization needs to be taken care of with purposeful consideration to crop and farm context. The advisory interactions must determine the crop, its growth stage, the management issue, and other farm conditions and then provide guidance. The reaction ought to describe what influence these details have on the recommendation. Contextual adaptation can become observable and more assessable through such a process. It could also enable the farmers to know whether a crucial condition has been misconstrued. The intended purpose is recommendation which will respond to the management query with a sufficient specificity to aid in a prudent decision.

Service evaluation should have information quality at its core. Assessment may take into account the clarity of the recommendations, the level of details, relevance, currency, internal consistency and the attitude to the recommendations as being correct. The two dimensions need to be looked at as a unit since a response might do well on one dimension, but still be hard to use on another one. The background and relevance of recommendations, in particular, would involve agricultural expertise. The results of the study justify the perception of informational performance as a fundamental service result and not a secondary characteristic of an intelligent interface (Yogita Kharde *et al.*, 2022).

The framework is applicable to organizing assisted advisory interactions by extension organizations. A farmer may talk to an officer or a service provider to explain circumstances, decipher suggestions, and evaluate viable management choices. This position aligns with mixed points of access to the sample and the significance of information quality (Renushe *et al.*, 2023). The support should help the farmer to comprehend the piece of advice

and how it relates to the decision. The ensuing interaction can retain the responsibility of the farmer on the final decision besides enhancing information with which that decision can be made.

The theoretic contribution is to decompose two service attributes and determine a common mediating mechanism. The concepts of accessibility and personalization are different, have different descriptive assessments, and structural coefficients (Naresh *et al.*, 2020). Their positive indirect relationships, however, all lead to the same point; information quality. This structure offers a description of the relationship between service design and informational evaluation and perceived decision performance. The fact that the information pathway is not conclusive of the associations that are represented by access and contextual adaptation in the given model is also reflected in complementary partial mediation.

CONCLUSION

This research paper discusses the AI-based agricultural advisory services in terms of accessibility, personalization, and quality of information and quality of crop management decisions among 430 users of this type of advisory services in Bangladesh. The interpretation made of four reflective constructs is supported with the measurement assessment. The reported analysis supports all five direct hypotheses and both mediation hypotheses. The most direct relationship is between information quality and decision quality, and the other two variables have both direct and indirect relationships with decision quality. Information quality variance and decision quality variance are explained with the model as 42.19 percent and 49.55 percent, respectively.

The main finding is that the characteristics of the advisory services are inextricably linked to the quality of the decision based on how the farmers assess the information. Practical relevance of convenient access and contextual adaptation is where they assist in providing content, which can be understood and utilized by farmers in evaluating management options. Agricultural advisory development must thus amalgamate available service agreements, purposeful personalization, and direct emphasis on informational performance. The results provide a consistent statistical explanation of the relationships and situate information quality at the heart of effective support of perceived quality of crop management decision.

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