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Household-specific targeting of agricultural advice via mobile phones: Feasibility of a minimum data approach for smallholder context

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A B S T R A C T

In recent years, agricultural extension services in developing countries have increasingly introduced modern information and communication technologies (ICT) to deliver advice. But to realize efficiency gains, digital applications may need to address heterogeneous information needs by targeting agricultural advisory contents in a household-specific way. We explore the feasibility of an automated advisory service that collects household data from farmers, for example through the keypads of conventional mobile phones, and uses this data to prioritize agricultural advisory messages accordingly. To reduce attrition, such a system must avoid lengthy inquiry. Therefore, our objective was to identify a viable trade-off between low data requirements and useful household-specific prioritizations of advisory messages. At three sites in Ethiopia, Kenya, and Tanzania independently, we collected experimental preference rankings from smallholder farmers for receiving information about different agricultural and livelihood practices. At each site, we identified socio-economic household variables that improved model-based predictions of individual farmers' information preferences. We used the models to predict household-specific rankings of information options based on 2–4 variables, requiring the farmer to answer between 5 and 10 questions through an ICT interface. These predicted rankings could inform household-specific prioritizations of advisory messages in a digital agro-advisory application. Household-specific "top 3" options suggested by the models were better-fit to farmers' preferences than a random selection of 3 options by 48–68%, on average. The analysis shows that relatively limited data inputs from farmers, in a simple format, can be used to increase the client-orientation of ICT-mediated agricultural extension. This suggests that household-specific prioritization of agricultural advisory messages through digital two-way communication is feasible. In future digital agricultural advisory applications, collecting little data from farmers at each interaction may feed into learning algorithms that continuously improve the targeting of advice.

1. Introduction

As mobile networks and devices approach ubiquity across the Global South, agricultural extension services increasingly employ modern information and communication technologies (ICT) to deliver advice to smallholder farmers (Baumüller, 2018; ITU, 2017). Many ICT-mediated agro-information applications have recently been created around the world, such as SMS-based market information services or

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call centers for technical farm advice. These new services allow disseminating technical, meteorological, or market-related information to large numbers of farmers in a timely and cost-efficient manner, no matter their spatial distance to extension centers, or the advisor-farmer ratio (Aker, 2011; Baumüller, 2018; Deichmann et al., 2016). Several challenges have become apparent, however, from the implementation of the first generation of ICT-supported extension services. Disseminating generic information to farming households with heterogeneous information needs and preferences may affect the relevance and trustworthiness of advisory messages, and sometimes led to poor effects on farmers' decision-making (Aker et al., 2016; Glendenning and Ficarelli, 2012). Moreover, although delivering information through ICT is often cheaper than through conventional face-to-face extension formats, it still has a cost (Aker, 2011). Thus, to achieve desired effects on farming in a cost-efficient way, ICT applications need to specifically target disaggregated advisory contents to suitable user groups.

Through automated two-way communication interfaces, such as interactive voice response (IVR) or USSD message exchange, digital services can enable farmers to individually select preferred contents from a body of agricultural advisory messages. But the enormous variety of potential information options, especially for agronomic advice, may cause lengthy menus that can be tedious to farmers, cost time or airtime, and may thus cause attrition. Speech recognition software and artificial intelligence could help to select advisory contents according to farmers' questions, but language diversity, local dialects, and background noise cause challenges (Plauché and Nallasamy, 2007). Thus, to avoid tedious menus, while suggesting individually suitable innovation to farmers, it may be necessary to reduce the number of information options and pre-select messages that are likely to be most relevant to the user.

Agricultural extension often responds to farmers' heterogeneous information needs by targeting alternative recommendations to different types of farmers, using complex household categorizations based on characteristics such as location, resource endowments, or dominant livelihood strategy (Berre et al., 2019; Kuivanen et al., 2016). But prioritizing agricultural information for the different household categories requires extensive qualitative fieldwork, which would usually be too much effort to still warrant the efficiency gains that ICT are employed for in agricultural extension (Schindler et al., 2016). As a shortcut, information targeting can already be improved with limited, simple information about the household, such as age and gender of the household leader (Khatri-Chhetri et al., 2017). ICT applications make it possible to collect such household information remotely through users' mobile devices, and integrate the delivery of accordingly selected information in a single two-way process (Dillon, 2012; Hartung et al., 2010). It is not clear, however, how such household-specific targeting through digital channels can be done in practice. Two key decisions seem necessary: (1) which information needs to be collected from farmers, and (2) how that information should be translated into household-specific prioritizations of different agricultural advisory contents.

To achieve practical usability, an important consideration is to reduce the burden of household data collection for farmers as much as possible. But reducing the amount of household data underlying targeting may affect the fit of targeted advisory messages to households' information needs and preferences. Thus, effective use of ICT in agricultural extension implies a pragmatic balance between rapid, data-sparse household data collection and the household-specificity of advice. Effective targeting requires requesting household information from farmers that is highly predictive of their information needs as well as maximizing data quality, e.g. by recalling a low number of simple, reliable and unambiguous household indicators from farmers (Hammond et al., 2017; Jarvis et al., 2015). In this study, we investigated the feasibility of household-specific information prioritization in agricultural advisory based on simple indicators collected from farmers through ICT. Our objective was to identify a viable solution for the trade-off between minimal data enumeration and useful household-specific targeting of agricultural advisory messages.

We investigated the feasibility of such a minimum data approach to household-specific targeting in three steps. First, we used a ranking exercise to collect data on smallholder farmers' information preferences about various agricultural and livelihood development practices. We assume that a farmer's stated information preferences correspond to different expected utilities of delivering advice on these topics. Second, we fit a model to the preference data and identified household characteristics that partly explained these rankings. These characteristics were taken from a lean indicator survey, which emphasizes rapid, reliable and simple enumeration through ICT (Hammond et al., 2017). Third, we used the model to predict most likely preference rankings of further households, based on their levels of the predictor variables. These predicted preferences for information options should then inform household-specific prioritizations of advisory messages, in a two-way ICT application that collects limited data from farmers. We repeated the research process independently at three sites in Eastern Africa. By comparing the experimental stated rankings (what farmers want) and the individual predicted rankings (what the model suggests), we assessed the usefulness of our approach against an alternative scenario of no targeting. We report outcomes and discuss their implications for integrating the collection of household indicators and the prioritization of agricultural advice in a single data-sparse ICT application, such as an automated telephone line.

2. Technology background

This study on the feasibility of a minimum data approach was conceived in the context of the design of a particular digital information system. In ongoing research at three sites in Eastern Africa, we are testing a new ICT-mediated information system for sustainable intensification of smallholder agriculture. A library of audio messages about diverse agricultural topics, previously recorded by extension agents, researchers, and experienced farmers, can be accessed through telephone calls (Fig. 1). To decide which topics, out of a large pool of messages, to suggest to the calling farmer, the system requests the entry of household data through a hierarchic IVR menu ("Press 1 for A, press 2 for B…"). Farmers hear questions (e.g. about gender or location) and provide answers through their telephone keypads. But lengthy enumeration of household data may also cause attrition. Therefore, we were interested in minimizing the number of questions required to generate useful household-specific prioritizations of alternative advisory messages.

3. Methods

3.1. Study sites

We carried out research at three East African sites (Fig. 2). By performing three independent case studies, we tested the feasibility of our approach and its robustness under contrasting circumstances. The three research sites differ in their agro-ecological and socio-economic conditions as well as in the levels of smallholder farmers' access to and experience with ICT. The Tigray region in Ethiopia is characterized by mostly arid climate and a unimodal rainfall regime, frequently experiencing droughts. About 80% of the population depend on agriculture, which is dominated by mixed smallholder cereal-livestock systems. Food insecurity rates are high (Gebrehiwot and Van der Veen, 2013). Makueni County in Kenya has predominantly semi-arid climate and a bimodal rainfall pattern, with recurrent drought events. Farming systems are primarily based on maize, cow pea, green grams, and grazing livestock (Speranza et al., 2010). The Southern Agricultural Zone in South-Eastern Tanzania comprises the administrative regions of Lindi and Mtwara, as well as Tunduru District of Ruvuma Region. Climate is tropical with a varyingly uni/bimodal rainfall distribution. Agriculture

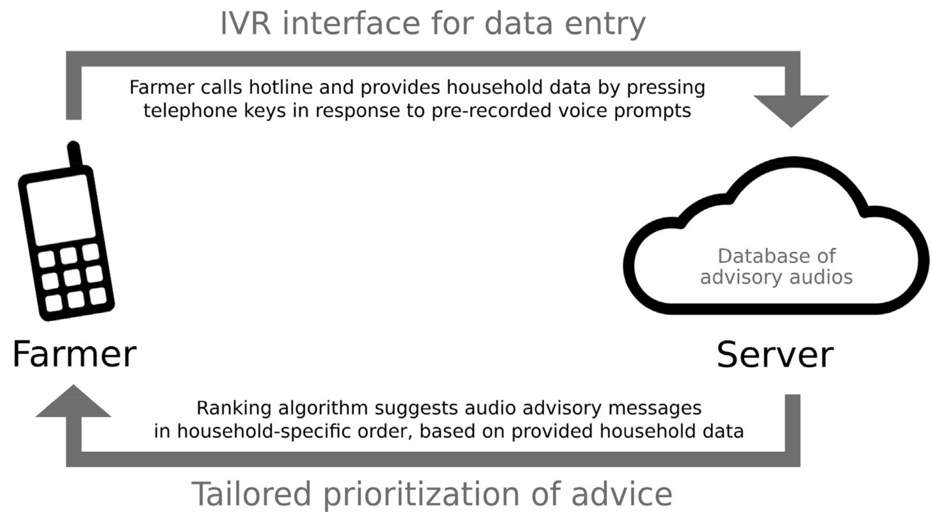

Fig. 1. Schematic overview of the intended information exchange between farmers and the online database of advisory audio messages, accessible through telephone.

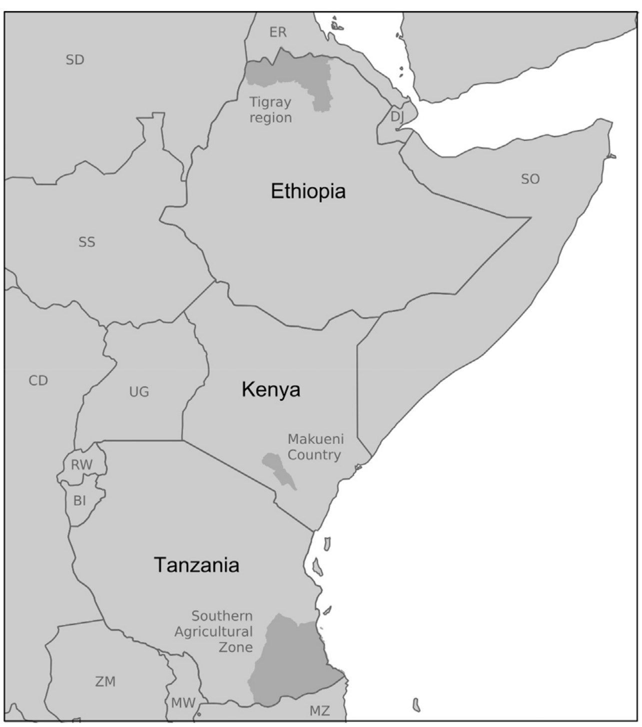

Fig. 2. Research sites in Eastern Africa. Neighboring countries are marked with ISO two-letter country codes. Spatial data retrieved from gadm.org.

concentrates on maize, cassava, and pulses for subsistence and commercial production of oil seeds (Perfect and Majule, 2010). Yields of staple crops are among the lowest at country level (Rowhani et al., 2011). In the remainder of this study, the sites are referred to by the country they are situated in.

3.2. Household surveys

Because we were interested in linking farmers' preferences for receiving different advisory contents with household characteristics, we first carried out country-specific variants of the "RHOMIS" lean indicator household survey (Hammond et al., 2017). This survey was designed for ICT-mediated enumeration using Open Data Kit software (Hartung et al., 2010), and intends to minimize respondent fatigue and resulting data inaccuracy by using simple questions about observable criteria. The data included variables related to household composition, resources, and the farming system. At each site, enumerator teams used smartphones to collect the data. Households were randomly sampled from beneficiary villages involved in an ongoing research project led by Bioversity International by sampling a country-wise constant number of smallholder farmers per village. 249 households were successfully surveyed in Ethiopia, 316 households in Kenya, and 521 households in Tanzania. Median farmer-stated land holdings were 0.61 ha in Ethiopia, 2.43 ha in Kenya, and 2.84 ha in Tanzania.

3.3. Experimental elicitation of farmers' information preferences

To determine farmers' individual information preferences at each site, we used a choice experiment. Farmers were asked to rank 9 different household-level practices according to their interest in receiving more information about them. We then used these stated preferences to train a recommendation system.

As information options in the choice experiments, we prepared sets of practices that were locally viable but not yet widely adopted by farmers in the area. These selections included innovative or rare practices found with so-called "positive deviant" households (Steinke et al., 2019). The fact that these strategies have before been implemented by relatively successful farmers makes them likely to be generally interesting options for further farmers, although not all options may appear equally suitable to all farmers. Simpler methods could also be used to produce a list of information options, such as quick elicitations from lead farmers, experienced extension agents, or agricultural researchers. In the context of this study, however, our approach ensured that, for each site, there was a set of information options with a similar level of local relevance. The procedure we followed to identify the practices is described in more detail in the supplementary information to this article.

Through a simple ranking experiment, we then determined farmers' individual preferences for information about 9 alternative information options. All options were illustrated on individual, roughly hand-sized cards. We randomly sampled household leaders from the initial RHOMIS survey to become participants in our ranking experiments (n = 86 in Ethiopia, n = 43 in Kenya, n = 98 in Tanzania). We asked participants to order the cards in accordance to how strongly they would like to learn more about the illustrated practices and recorded the ranking orders (Fig. 3). In most cases, this involved further on-spot explanations about the practices by the enumerators. For data exploration, we analyzed the internal heterogeneity of rankings at each

Fig. 3. Enumeration of farmers' information preferences in Ethiopia.

study site by Kendall's W, a coefficient of rank concordance (Kendall and Babington Smith, 1939), using the package *irr* (Gamer et al., 2012) in the R software (R Core Team, 2018). We interpreted Kendall's W using the classification system by Schmidt (1997).

3.4. Analysis of preference data

3.4.1. Estimation of overall most likely rankings of information options

At each site, we first identified the most likely overall preference ranking across all respondents (n = {86, 43, 98}) by fitting a Bradley-Terry model to farmers' stated rankings (Bradley and Terry, 1952). Bradley-Terry models identify the overall most likely order from multiple rankings of the same items. Because Bradley-Terry models rely on pairwise comparison data, we first converted the rankings to a pairwise comparison data format. Converting rankings to pairwise comparisons involves an information loss, but allows statistical analysis with covariates (ranker characteristics), using the generalized linear model framework (Dittrich et al., 2000). In contrast to the Bradley-Terry model, the Plackett-Luce model analyzes rankings directly (Luce, 1959; Plackett, 1975). Currently available implementations of the Plackett-Luce model, however, do not follow the generalized linear model framework and the partitioning-based framework has limited statistical power (Turner et al. 2018). To get a quantitative idea of the potential information loss caused by converting rankings to pairwise comparisons, we compared rankings and preference scores generated by Bradley-Terry models and Plackett-Luce models, respectively (for detail, see following Section). We used the packages *BradleyTerry2* (Turner and Firth, 2012) and *PlackettLuce* (Turner et al., 2018) in the R software (R Core Team, 2018). The maximum likelihood parameter estimates (log-odds) of the practices ranked by each Bradley-Terry and Plackett-Luce models had Pearson's correlation coefficients between 0.77 (Tanzania) and 0.96 (Ethiopia), suggesting that the information loss is moderate to small.

3.4.2. Estimation of overall preference scores of information options

The Bradley-Terry model uses maximum likelihood to estimate the log-odds of options being ranked higher than a reference option, which is arbitrarily set to 0. We converted these values into probabilities, and then calculated, for each information option, the probability of being ranked higher than all other options (the relative "preference score") by iteratively modifying the reference, following the procedure described by Jeske et al. (2007). We then identified sets of practices that were ranked significantly different by the farmers by testing which of the pairwise differences in preference scores of practices were significantly different from 0. For this, we corrected the p-values for multiple comparisons using Holm's sequential Bonferroni procedure (Holm, 1979).

3.4.3. Model specification with household variables

Our ultimate goal was to predict the most likely individual preference rankings for further target households. These predicted rankings would then inform household-specific prioritizations of advisory messages. For this, we needed models that linked rankings with household characteristics. Therefore, we further specified the Bradley-Terry models by introducing socio-economic household variables as covariates. Candidate covariates were selected following two criteria. Our first criterion was that variables should be known to affect the applicability of specific agricultural practices and/or farmers' preferences for agricultural information (e.g. Berre et al., 2019; Kassie et al., 2009; Khatri-Chhetri et al., 2017). Our second criterion was that the variables should be based on a limited number of simple questions, to allow rapid data collection through a digital interface. We did not consider variables that require more than 7 separate question in the RHOMIS framework (see Section 3.2 above). This criterion meant we did not consider some potentially important variables, such as financial resources or market orientation, for which more detailed series of questions are required to generate reliable data (Hammond et al., 2017; Hanisch, 2005). The resulting selection of candidate covariates is shown in Table 1. These included three basic household variables (gender, age, region), four proxies of productive resource availability, and three variables reflecting (dis–)investments into agricultural intensification, roughly corresponding to different "farming styles" (Van der Ploeg and Ventura, 2014). For Ethiopia and Tanzania, there were 10 candidate variables, while for Kenya there were 9. In Kenya, the survey covered only one administrative region, so region was omitted as a covariate for Kenya.

We then specified models by forward variable selection using the "Permuted Inclusion Criterion" (Lysen, 2009). This procedure consists of two steps. In the first step, we added to the set of original covariates an additional set of fake variables generated by randomly permuting the original variables. As a result, every farmer ranking of practices was linked to a set of observed variables and a set of permuted variables, i.e. the characteristics of another randomly selected farmer. Permuted variables were not expected to have any predictive power for rankings. In the second step, we added covariates to the Bradley-Terry model. We added each variable (real and permuted) to the null model separately and recorded which of the variables reduced model deviance most strongly. We replicated this process 500 times, each time with a new random permutation. Across the 500 runs, we identified the covariate that appeared most often as the most deviance-reducing one. When this was a real variable, we added it to the model, excluded the corresponding permuted variable from data, and continued forward selection. We stopped covariate selection when a permuted variable was found to be the most frequent most deviance-reducing variable, i.e., when no real variable had more explanatory power than the fake ones. The relative influence of different household characteristics on farmers'

Table 1
Candidate covariates used in specification of Bradley-Terry models of farmers' information preferences.

Variable category	Variable	Definition (unit)	Number of survey questions needed
Basic household variables	Gender of household head	Female, Male	1
	Age of household head	(years)	1
	Region	2 options in Ethiopia, 1 in Kenya, 2 in Tanzania	1
Resources	Land holdings	(ha)	1
	Labour availability	Household size (in MAE) divided by land holdings	7
	Livestock holdings	(Tropical livestock units)	6
	Social capital	First loading of a principal component analysis on indicators of membership in established groups, and access to public benefits	3
Farming style-related	Land tenure	Household owns land: yes/no	1
	Labour hiring	Household ever hires workers for farming: yes/no	1
	Input changes	Household has changed the use of agricultural inputs over the last year: Decrease/No change/Increase	1

preferences was quantified by the respective step-wise changes in model deviance caused by including each variable in the model. We rescaled the values by setting the highest value to 1.

We assessed goodness-of-fit of the models by reduction in model deviance compared to the null model (no covariates). In addition, we calculated the mean pairwise agreement between individual stated rankings and the rankings predicted for the same farmers based on their household characteristics. For this, we used Kendall's tau, a coefficient of similarity between two rankings (Kendall, 1938). Kendall's tau can take values from −1 (inverse ranking) to + 1 (identical ranking). We used the package *Kendall* (McLeod, 2012) in the R software (R Core Team, 2018).

3.5. Generating household-specific prioritizations of information options

As a final step, we used the fit models to predict the most likely preference rankings for all households enumerated in the RHOMIS surveys (n = {249, 316, 521}, see Section 3.2). This generated a household-specific prioritization of the information options for each household, based on the characteristics previously identified as predictors.

We assessed the usefulness of these household-specific prioritizations in three ways, always comparing farmers' stated preference rankings (training data from n = {43, 86, 98} farmers) and the household-specific model outputs for these same farmers. Firstly, we calculated the mean Kendall's rank correlation (Kendall's tau) between stated and predicted preference rankings (see above). Secondly, we specifically explored the consequences of using the prioritizations to make individual "top 3" suggestions to target households. We assessed the match between the 3 options ranked highest by respondents, and the "top 3" suggested by the fit models for these particular farmers by counting the options in agreement, regardless of the particular rank positions within each set of three. Thirdly, we differentiated these agreement scores by the 9 information options. For each option, we calculated the probability of being correctly included in the "top 3" suggestions for respondents who had included that practice in their "top 3" preferences.

To compare the model-based targeting approach with a no-targeting alternative, we also assessed the usefulness of random prioritizations. For this, we generated a random order of the information options for each household and performed the same three steps of analysis as for the model-based prioritizations. We repeated this process 1000 times and always calculated mean scores from 1000 runs.

4. Results

At all study sites, farmers expressed heterogeneous preferences for agricultural information (Fig. 4, left side). There was moderate overall agreement in ranking the information options among Ethiopian and Kenyan respondents (Kendall's $W \approx 0.5$), but preferences were more differentiated in Tanzania (Table 2). Nonetheless, at all sites, Bradley-Terry models identified significantly different preference scores for the information options (Table 2). In Ethiopia, practices could be categorized into four distinct groups with significant differences between their positions in farmers' rankings. In both Kenya and Tanzania, there were three groups of practices (Table 2).

At each site, farmers' rankings were associated with certain socio-economic characteristics (Table 3). A specific set of two to four household characteristics reduced Bradley-Terry model deviance and explained part of the variation in preferences for agricultural information. Variables that partly explained preferences included: Age of the household head, Region, Labour availability, Social capital, and a recent change in agricultural input use. Of the 10 variables we tested, however, 5 did not contribute to model fit in any of the country cases: Gender, Land holdings, Livestock holdings, Land tenure, and Labour hiring.

Using the identified household variables as predictors, the Bradley-Terry models determined a most likely preference ranking for each surveyed household (Fig. 4, right side). These predicted rankings were less differentiated than the stated rankings, with Kendall's W of 0.85 in Ethiopia, 0.86 in Kenya, and 0.81 in Tanzania. On average, pairwise agreement between farmers' stated preference rankings and model-predicted rankings based on the respective farmer's characteristics was moderate to strong (mean Kendall's tau ranging from 0.30 to 0.47, Table 3).

These predicted household-specific prioritizations varied according to the households' characteristics: For example, for Ethiopian households that had recently *increased* their agricultural input use, predictions set the option "Finding an off-farm job" at an average rank of 7.7. For households that had recently *decreased* input use, this option was deemed more suitable, with an average predicted rank of 4.3. In Tanzania, the Bradley-Terry model suggested "Intercropping maize/pigeon pea" as top option for 83% of the recent input *increasing* households, whereas it gave highest priority to "Improving crop storage" for all input *decreasing* households.

Comparing the stated rankings with both random rankings and model-predicted rankings showed that household-specific "top 3" information options suggested by the models were better fit to farmers' preferences than the "top 3" of a random order (Table 4). Suggesting to each farmer a random selection of 3 out of 9 options would include, on average, 1 of the farmer's three most-preferred options. With household-specific prioritizations generated by the fit Bradley-Terry models, the "top 3" options included an average of 1.48 (Tanzania) to 1.68 (Kenya) of the farmers' three most-preferred options (regardless of the

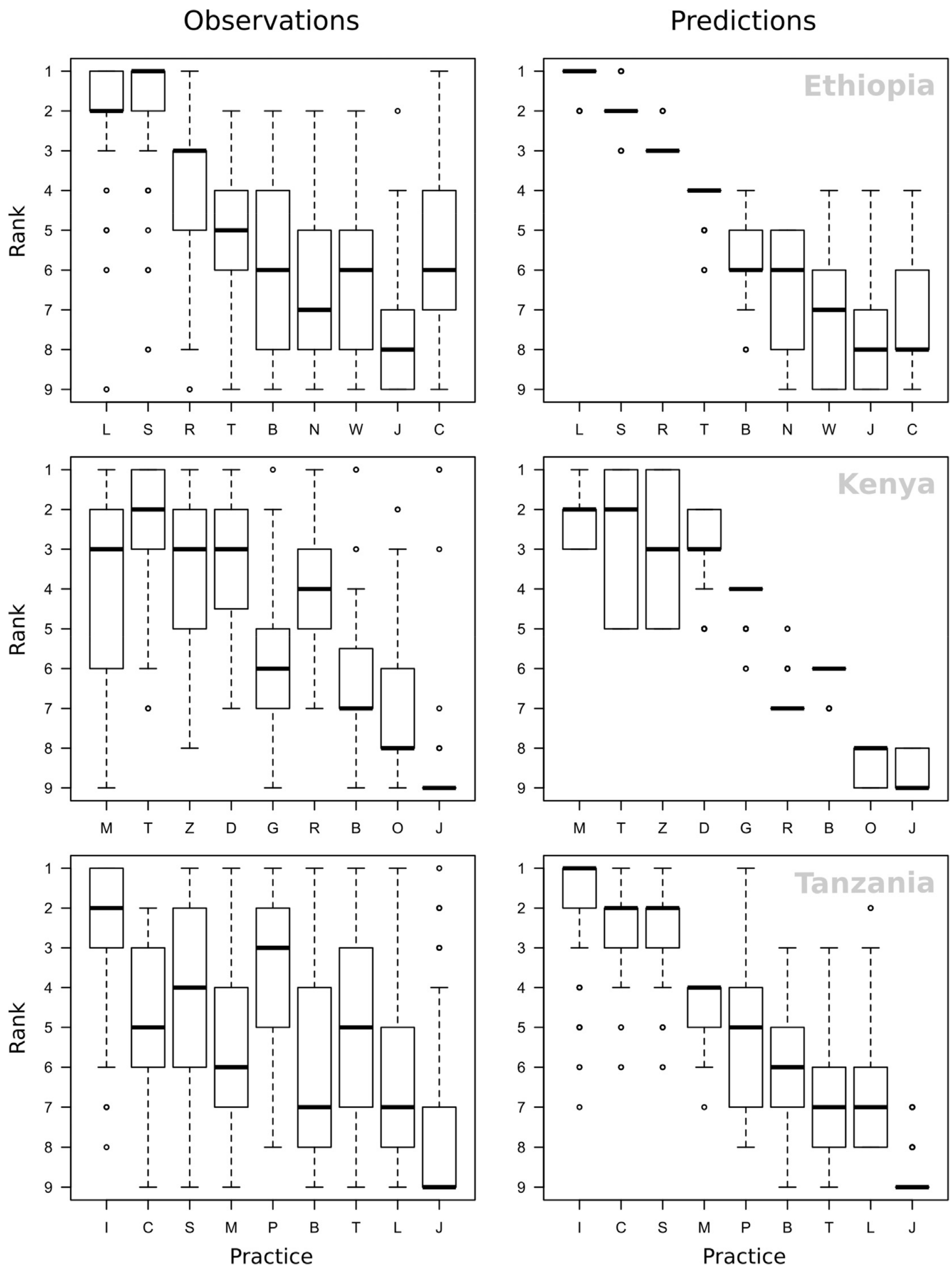

Fig. 4. Stated rankings (left) and rankings predicted by the fit Bradley-Terry models (right). For the practice codes on horizontal axes, see Table 2. n(observations) = 86 in Ethiopia, 43 in Kenya, and 98 in Tanzania. n(predictions) = 249 in Ethiopia, 316 in Kenya, and 521 in Tanzania.

specific rank within the set of three). Across all tested households at all three sites, this mean agreement between stated and model-predicted “top 3” options was 1.54. With model-based targeting, the probability of suggesting to farmers at least 2 out of their 3 most-preferred options was more than doubled in Ethiopia (a 52% chance instead of 22% without targeting) and Tanzania (49% instead of 23%). In Kenya, where farmers’ preferences showed stronger variation among the most-preferred information options, the relative benefit of model-based targeting over random suggestions was weaker, but still evident (65% versus 49% without targeting). At all sites, targeting reduced the probability of a “complete miss”, i.e. including none of the farmers’ 3 most-preferred options in the “top 3” suggestion. In Ethiopia, for example, the probability for this to happen was 5%, compared to 24% in a no-targeting scenario.

5. Discussion

5.1. Small sets of household variables help to predict information preferences

This study demonstrates that relatively little household data can be sufficient to anticipate farmers’ individual preferences for agricultural

Table 2
Agricultural and livelihood practices identified with "positive deviant" households and mean Bradley-Terry parameter estimates for farmers' preference rankings of information about these practices. In groupings of practices, different letters indicate significantly different ranks of information options.

Information option [a]	Code (Fig. 4)	Kendall's *W* of all rankings	Preference score	Grouping
Ethiopia (n = 86)		0.482		
Sowing cereals in lines	L		0.806	a
Diligent farm scheduling	S		0.780	a
Rain water harvesting	R		0.671	b
Storing and trading crops	T		0.512	c
Opening a business	B		0.375	d
Tree nursery	N		0.361	d
Reducing food wastage	W		0.351	d
Finding off-farm job	J		0.329	d
Improving crop storage	C		0.314	d
Kenya (n = 43)		0.495		
Machine tillage	M		0.764	a
Terracing	T		0.726	a
Zai pits	Z		0.712	a
Dry planting	D		0.673	a
Collective crop marketing	G		0.500	b
Mulching	R		0.438	b
Opening a business	B		0.380	b
Renting out traction animals	O		0.168	c
Finding off-farm job	J		0.139	c
Tanzania (n = 98)		0.318		
Intercropping Pigeon pea/Maize	I		0.675	a
Improving crop storage	C		0.645	a
Diligent farm scheduling	S		0.636	a
Machine tillage	M		0.492	b
Intensifying poultry production	P		0.460	b
Opening a business	B		0.450	b
Tree nursery	T		0.427	b
"Livestock bank"	L		0.426	b
Finding off-farm job	J		0.287	c

[a] For explanations about the practices see the supplementary information to this article.

Table 3
Goodness-of-fit parameters of Bradley-Terry models of farmers' information preferences. Predictor weights represent relative reductions in residual deviance through a deviance-based forward selection procedure and are scaled by setting the maximum value to 1.

Model parameters	Ethiopia	Kenya	Tanzania
Null deviance	3693.1	1297.6	4541.5
Residual deviance	2858.0	845.5	4144.0
Degrees of freedom	2616	904	3236
Mean Kendall's tau between stated and predicted rankings	0.47	0.38	0.30
Predictor weights			
Age	0.728		0.443
Administrative region	0.615		
Labour availability	0.821	0.956	
Social capital			0.104
Input changes	1.000	1.000	1.000

information in a way that allows usefully customized prioritizations of advisory messages. Although predicted rankings were not perfectly congruent with observed preferences, the models made household-specific suggestions that were, on the whole, better-fit to farmers' preferences than random recommendations. The socio-economic household variables associated with information preferences differed between sites, which also involved different tested portfolios of information options. But overall, having implemented a recent change in agricultural input use, such as chemical fertilizer or improved seeds, was the strongest predictor across all sites, as well as the only universal one. This suggests that a household's "farming style" may be more important information for prioritizing household-specific development strategies than its access to productive resources, which many farm typologies rely on. Indeed, despite similar resource endowments, farmers may seek highly diverse development strategies, e.g. in function of their risk aversion or the dominant output sought after, such as increasing cash income or sustaining food production (Van der Ploeg and Ventura, 2014). This finding has implications for the design of digital extension applications that target advice: Enumerating household resource endowments through ICT may be easier than collecting information on farming styles, which can be hard to collect through numeric data or yes/no questions (Fairweather and Klonsky, 2009). Nevertheless, our analysis suggests that adequate targeting of advice should use data on target farmers' farming styles. This could include, for example, information about fertilizer purchases or recent on-farm investments.

5.2. Useful prioritization of advisory messages based on data enumerated through ICT seems feasible

To assess the usefulness of the model-based targeting approach presented here, an important question is whether it can reduce the risk of disseminating information of low relevance. This is a crucial criterion for the design of digital advisory services (Nakasone et al., 2014). Our analysis explored the scenario of delivering customized "top 3" suggestions of agricultural advisory contents. Compared to random suggestions, the share of farmers receiving predominantly irrelevant messages was greatly reduced at each site (e.g. from 51% down to 36% in the weakest case, Kenya). Overall, through the targeting approach, a majority of households received "top 3" suggestions that were better-fit to their preferences than random orders.

Although an initial data collection effort is needed to train the first model, the benefit of delivering targeted advice to a large number of households may justify the execution of the ranking exercise with a limited number of farmers. Because predictor variables are not universal, model predictions are valid only for the study region, and only

Table 4
Selecting "top 3" suggested information options either by Bradley-Terry models or at random: Mean agreement with farmer-ranked top 3, and probabilities of individual information options being correctly included in "top 3" suggestions.

		Ethiopia			Kenya			Tanzania		
		n = 82[a]			n = 31[a]			n = 91[a]		
			Targeting	Random		Targeting	Random		Targeting	Random
Mean agreement between observed and predicted preferences			1.55	1.00		1.68	1.00		1.48	1.00
Number of practices correctly included in "top 3"	3		9%	1%		13%	7%		5%	1%
	2		43%	21%		52%	42%		44%	22%
	1		44%	53%		26%	40%		44%	54%
	0		5%	24%		10%	11%		7%	24%
Information option suggested adequately		L	22%	30%	M	100%	20%	I	93%	32%
		S	74%	30%	T	67%	24%	C	84%	31%
		R	67%	31%	Z	69%	25%	S	97%	29%
		T	78%	31%	D	74%	20%	M	0%	33%
		B[b]	–	–	G	0%	26%	P	15%	32%
		N	30%	31%	R	0%	19%	B	0%	34%
		W	57%	32%	B	0%	18%	T	0%	29%
		J	0%	31%	O	0%	34%	L	0%	31%
		C	0%	34%	J	0%	11%	J	0%	30%

[a] Numbers of predictions are lower than numbers of recorded observations (Table 1) due to missing household data for some ranking households.
[b] No ranking household had included this option in their top 3.

for the practices originally included. In the future, analysis may be refined by fitting local sub-models through recursive partitioning (Strobl et al., 2011). Moreover, linking preferences to objective characteristics of practices (e.g. implementation costs, expected effects on labour availability) may allow introducing new practices to the prioritization model and a resulting digital information service, without repeating the ranking experiment. This study demonstrates that even with a relatively small sample of farmers training the initial model, improved targeting of a set of initial advisory messages is possible. Over time, as farmers start using an ICT-mediated information system and make choices – e.g. about the most-preferred out of a set of three promoted practices – the household-specific suggestions of promoted practices could be further refined. Each time a farmer calls, they might be asked 1–2 additional questions about their household and farming system. As the sample size grows and more household data, as well as partial ranking choices, enter the model, the system will increase its predictive power, potentially also using more predictor variables not included in this study. An initial targeting model, informed by the choice experiment with representative households, would be needed to offer first-time users an acceptable experience, to encourage usage of the service. Over time, learning algorithms or regular manual adjustments to the model should use newly accumulating data to continue to improve the targeting of agricultural advice.

But does the improvement in targeting advice justify the enumeration effort on the farmer side? At each site, the models generated prioritizations based on two to four household variables. These variables were calculated from sets of 5 (Tanzania) to 10 (Ethiopia) questions. The most important variable, recent changes to agricultural input use, requires only one question. Mini-questionnaires of a few questions can be implemented through ICT, e.g. via USSD menus or interactive voice response, both of which request users to enter data through the keypad of conventional mobile phones ("Press 1 for topic A, press 2 for topic B …"). Through recent developments in mobile money services, mobile phone users across the Global South are becoming increasingly acquainted with these technologies (GSMA, 2017). Designers of new agro-advisory services will need to identify a viable trade-off between questionnaire length and predictive power of the information for household-specific targeting of advisory contents. Our results suggest that prioritization of advice through ICT tools is possible, and that a satisfactory trade-off can be achieved between rapid, simple household data enumeration and useful household-specific prioritizations. The rise of smartphone ownership among rural population worldwide likely offers even more opportunities for household- and even plot-specific targeting of agricultural advice, taking additional benefit of features such as GPS or video (Carmona et al., 2018).

Household data used in this study was collected using ICT (Open Data Kit on mobile Android devices), but not entered by farmers themselves. Although the lean indicators in the RHOMIS survey were designed for simple and unambiguous enumeration, this might mean that farmers can face unexpected difficulties in providing the requested household information without prior training (Lerer et al., 2010; Patnaik et al., 2009). In ongoing research, we are observing farmers' interaction with the IVR interface, in order to make necessary adaptations to the sequence of data entry or IVR voice prompts.

5.3. Farmers' overall information preferences can suggest priority-setting for advisory services

Our results suggest that information on farmers' information preferences, which may also accumulate as farmers use a digital agro-advisory application and make choices, can generate more general, useful insights for advisory services. Despite heterogeneity in respondents' rankings, at each site, the Bradley-Terry models identified distinct groups of practices that were given significantly different priority by the farmers. Such categorization of information options by overall popularity can be useful for extension services, e.g. to select topics about which to provide particularly detailed information. For example, strong overall interest in line sowing in Ethiopia may warrant providing multiple, crop-specific messages about line spacing. Because there is a trade-off between the need for disaggregating information according to farmers' preferences and the costs of generating contents, knowing which topics to emphasize in greater detail can be important for the financial sustainability of digital advisory applications (Nakasone et al., 2014).

Across all sites, practices related to own agricultural production were generally preferred over non-agricultural options. This finding underlines the need for advisory support to established household activities, rather than diversification of rural livelihoods. In particular, "Finding off-farm job" was of little interest to the responding farmers. This seems to contrast calls for supporting non-agricultural income options in rural development, which are often based on sound econometric analysis (e.g. Frelat et al., 2016), but may face challenges in practice due to farmers' livelihood preferences and aspirations (Verkaart et al., 2018). Our results support the idea that pure information interventions without practical demonstration activities – such as the provision of audio messages through a hotline – may be most effective by focusing on knowledge-based, gradual modifications of current systems. When farmers need to make investments, e.g. in labour or machinery, information interventions may nevertheless need to be accompanied by additional measures, such as insurance schemes (Pradhan et al., 2015).

6. Conclusions

This study demonstrates the feasibility of useful household-specific prioritizations of agricultural information based on small sets of household indicators collected through ICT. Although training the first models with experimental and survey data from representative households requires an initial effort, this may contribute to resource-efficient strategies of engaging ICT in agricultural extension. We found that it is possible to achieve a satisfactory trade-off between minimal data enumeration, which is required if farmers are to use ICT for access to advisory services, and the household-specific adaptation of advice. This approach is especially useful to deliver a first set of relevant content to farmers, who could be asked for some information when registering to the service. Once farmers start using the service, the digital system itself may continuously generate new data about users' preferences and characteristics, thus improving the model-based targeting with new training information.

In the context of the particular digital solution we are considering (Section 2), this supports the idea that it is feasible to deliver individually targeted agricultural information to heterogeneous households through an automated call-in hotline connected to a database of audio records. An interactive voice response menu, requesting farmers to answer a low number of questions using their telephone's keypad, may enable ICT applications of this kind to select suitable advisory contents. To justify investments into new services, further research needs to establish to what extent a household-tailored advisory application increases adoption and continued use of promoted practices, compared to more "one-size-fits-all" approaches to agricultural advisory. Our results are also relevant for other applications that involve household-specific agricultural advice. In the future, research may produce more generalizable insights about which data-sparse indicators can serve as predictors of farmers' information needs. Small standard sets of questions that efficiently capture the factors behind farmers' information needs will likely be useful for a wide range of digital applications in agricultural advisory.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compag.2019.05.026.

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