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DEPARTMENT OF EARTH AND ENVIRONMENTAL SCIENCES
KU Leuven - BELGIUM

Design of Digital Agricultural Extension Tools: Perspectives from Extension Agents in Nigeria

Oyakhilomen OYINBO, Jordan CHAMBERLIN and Miet MAERTENS

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Division of Bioeconomics
Department of Earth and Environmental Sciences
University of Leuven
Geo-Institute
Celestijnenlaan 200 E – box 2411
3001 Leuven (Heverlee)
Belgium
http://ees.kuleuven.be/bioecon/

Title

Oyakhilomen OYINBO [1], Jordan CHAMBERLIN [2] and Miet MAERTENS [3]

Abstract

In Sub-Saharan Africa, smallholder agricultural production takes place under heterogeneous conditions. Yet traditional extension systems mainly provide generalized recommendations to farmers which do not account for this. Using data from a choice experiment in Nigeria, we analyze the preferences of extension agents (EAs) for the design of ICT-enabled decision support tools (DSTs) for site-specific nutrient management recommendations. We find that EAs are in general very willing to use such DSTs and prefer a DST with a more user-friendly interface that requires less time to generate an output. Yet we also find heterogeneous preferences: some EAs care more about the effectiveness-related features of DSTs, such as information accuracy and level of detail, while others prioritize practical features, such as tool platform, language and interface ease-of-use. Recognizing and accommodating such preference differences may facilitate the adoption of DSTs by extension agents and thus enhance the scope for such tools to impact the agricultural production decisions of farmers.

Key Words: Agricultural extension, Choice experiment, Digital extension technology, Extension agents' preferences, Soil fertility management, Site-specific extension

JEL classification: O31, O33, Q16

Corresponding author: oyakhilomen.oyinbo@kuleuven.be

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[1] Division of Bio-economics, Department of Earth and Environmental Sciences, University of Leuven, Belgium
[2] International Maize and Wheat Improvement Center (CIMMYT), Nairobi, Kenya
[3] Division of Bio-economics, Department of Earth and Environmental Sciences, University of Leuven, Belgium

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1 Introduction

The use of chemical fertilizer and improved soil fertility management practices is low in SSA (Sub-Saharan Africa), which contributes to low yields in staple food crops (Theriault et al., 2018; Jayne et al., 2019; ten Berge et al., 2019). Information constraints play a role in this (Chianu et al., 2012; Benson and Moques, 2018; Shikuku, 2019). Empirical findings for different parts of SSA show that relaxing information constraints through agricultural extension services can improve technology adoption, productivity and farmer welfare (Dercon et al., 2009; Lambrecht et al., 2014; Pan et al., 2018; Makate and Makate, 2019). Yet, extension services do not always have the intended effects (Feder et al., 2004; Davis et al., 2008; Ragasa and Mazunda, 2018). Traditional extension systems largely provide very generalized soil fertility management information to farmers at national or regional scales (Theriault et al., 2018; Shehu et al., 2018; Ichami et al., 2019). Such information fails to take into account the spatial and temporal variability in biophysical and socio-economic conditions within a given national or regional context (MacCarthy et al., 2018; Jayne et al., 2019).

The use of digital decision support tools (DSTs), enabled by modern information and communication technology such as smartphones and tablets, is increasingly promoted for more effective delivery of agronomic information tailored to the site-specific conditions of individual farmers (Bernet et al., 2001; Kragt and Llewellyn, 2014; MacCarthy et al., 2018). Despite the potential of such DSTs to improve information delivery, their use remains low. Constraints are posed not only by farmers who might be reluctant to take up extensive advice from such tools, but also by extension agents who might be reluctant to use such tools (Hochman and Carberry, 2011; Ravier et al., 2016; Rose et al., 2016). Some advocate that encouraging uptake of DSTs would require design of DSTs to be driven by user-defined preferences via a co-design approach (Botha et al., 2017; Ditzler et al., 2018; Rose et al., 2018).

In this paper, we analyze the preferences of extension agents for the design of DSTs and their willingness to use such tools. We implement a discrete choice experiment among 320 extension agents (EAs) in northern Nigeria, where a new DST for site-specific nutrient management recommendations for maize, the Nutrient Expert (NE) tool was piloted in 2017 and

2018.[4] This allows us to have an *ex ante* understanding of the potential uptake of DSTs and the specific practical and effectiveness-related design features that are more (or less) appealing to EAs. In addition, it allows us to gain insights on the heterogeneous preferences for the design of DSTs, and the underlying sources of heterogeneity.

The contribution of this paper to the literature is twofold. First, it is worth noting that the literature on DST design is very thin, and we contribute to this by providing *ex ante* insights on optimizing design of DSTs from the perspective of EAs in Nigeria. To the best of our knowledge, the only quantitative *ex ante* study of EAs preferences for DSTs is on weed management in Australia (Kragt and Llewellyn, 2014). Our paper builds on the latter with a focus on a DST for nutrient management for maize, on a different farming system and on a developing country context. In addition, we use more recent data, a larger sample of EAs (about 200% larger) and take into account attribute non-attendance (ANA), a potential source of bias not considered in the previous study. Other studies on DSTs such as Rose et al. (2016, 2018) analyze the uptake of DSTs among farmers and EAs *ex post* in a qualitative way. They point to a lack of co-design in the development DSTs as a main factor contributing to low uptake of these tools. Ditzler et al. (2018) put forward a theoretical framework to assess extension tools and stress that the link between tool design and users of DSTs is important. Our paper complements this literature through an *ex-ante* quantitative assessment of the preferences of EAs for the design of nutrient management DSTs and their willingness to use such tools. Second, this study contributes to the choice experiment (CE) literature by adding to the scant empirical studies that implement CEs among EAs instead of the more common use of CEs for farmers and food consumers in agricultural economics. CE studies are gaining importance in agricultural economics; they are increasingly used to assess farmers' preferences for agricultural technologies prior to the spread of new technologies, and inform agricultural research (Breustedt et al., 2008; Asrat et al., 2010; Jaeck and Lifran, 2014; Lambrecht et al., 2015; Coffie et al., 2016; Van den Broeck et al., 2017; Dalemans et al., 2018; Gamboa et al., 2018; Arora et al., 2019). Yet, the use of CEs to inform agricultural extension *ex ante* is still very limited. Some studies use CEs to assess farmers' preferences for DSTs and their

[4] NE is being developed in Nigeria, Ethiopia and Tanzania as part of 'Taking Maize Agronomy to Scale in Africa (TAMASA)' project led by International Maize and Wheat Improvement Center (CIMMYT) in collaboration with International Plant Nutrition Institute (IPNI) and supported in Nigeria by the International Institute of Tropical Agriculture (IITA) and the Centre for Dry land Agriculture (CDA), Bayero University Kano. See Pampolino et al. (2012) and Oyinbo et al. (2019) for a detailed description of the tool.

willingness to follow extension advice from such tools (Oyinbo et al., 2019) but no CE study specifically focus on EAs except for Kragt and Llewellyn (2014). Our study extends the application of CE among EAs, and can potentially open up further research along this direction. This is important given the emerging policy interests in the evidence-based design of extension tools to support provision of advisory services.

The remainder of the paper is structured as follows: the next section describes the research area, and specificities of extension in the area, the choice experiment and the econometric estimation. Next, we report the results of the estimation, followed by a discussion and implications of the results. Finally, we report the conclusion of the paper in the last section.

2 Research Background and Methods

2.1 Research Area

The study area includes three states in northern Nigeria – Kaduna, Katsina and Kano – where maize is an important staple crop. It is grown across the northern Guinea, southern Guinea and Sudan savanna agro-ecological zones under a smallholder rain-fed cropping system. Maize yields on farmers' fields in the area are low, on average 1 to 2 tons per hectare despite potential yields of 5 tons per hectare and above (Shehu et al., 2018; ten Berge et al., 2019). Traditionally, provision of extension services rests on the public sector extension systems, implemented at the state level (Naswem and Ejembi, 2017). In our study area, these are the Kaduna state agricultural development agency (KADA), the Katsina state agricultural and rural development authority (KTARDA) and the Kano state agricultural and rural development authority (KNARDA). The relatively low extension coverage of the public extension systems has given rise to other non-governmental extension providers in recent years. Examples include increased private sector participation in the provision of advisory services (e.g. from input suppliers, input service providers, agro-dealers etc.) as well as non-governmental organizations such as Sasakawa-Global 2000 (Davis and Spielman, 2017; Gizaki and Madukwe, 2019). The extension systems in our study area, and in Nigeria at large, have not been seen as efficient in addressing site-specific information constraints despite the heterogeneous production conditions within the areas serviced (Naswem and Ejembi, 2017). A typical example is the provision of a general recommended fertilizer application rate of 120 kg N, 60 kg P_2O_5 and 60 kg K_2O per ha for maize in much of northern

Nigeria (Shehu et al., 2018). This context has prompted the development of DSTs such as NE and similar tools to enhance the capacity of the extension systems, and allow for the provision of site-specific agronomic recommendations.

2.2 Data Collection and Sampling

Data were collected through a discrete choice experiment (CE) and a survey among EAs in November 2016. The survey was implemented using a structured questionnaire with modules on demographics, work environment, experience with ICT, fertilizer recommendations and income sources. The CE is explained in the next section. We randomly selected 278 EAs from KADA, KTARDA and KNARDA, based on a full list of frontline EAs – i.e. EAs who directly advise farmers in the field – provided by the zonal extension offices. In addition, we randomly selected 42 EAs affiliated to private extension providers, again based on full list of frontline EAs from these institutions. The total sample includes 320 EAs working in the study area.

2.3 Choice Experiment Design and Implementation

We use a discrete CE as a stated preference elicitation method to assess EAs preferences and willingness to use DSTs *ex ante*. Respondents were presented with a sequence of choice sets, each having two discrete hypothetical alternatives of a DST, and asked to choose their most preferred alternative. The hypothetical alternatives are described by different attributes of the DST with levels that vary over the alternatives. CEs are rooted in random utility theory; the rationale is that utility is derived from the underlying attributes of a good or service rather than from the good or service *per se* (Lancaster, 1966) and that respondents choose those alternatives that offer the largest expected utility (McFadden, 1974).

Based on consultations with a number of scientists involved in the development of the NE tool for Nigeria, a detailed review of DST design literature and a series of meetings with EAs, we identified six relevant practical and content/effectiveness-related attributes (Table 1). The first attribute is ‘user-friendliness’, which relates to the user-interface of a DST and the ease of navigating through tool modules to generate an extension output. The second attribute, level of detailed output, relates to the number of different recommendations that result from the DST and that should be explained by the EA to the farmers as different options. Both are described by three levels: low, moderate, and high levels of user-friendliness and detailed output. The third attribute ‘predictive power’ relates to the accuracy of a DST in formulating fertilizer recommendations for a farmer to achieve a certain yield. It is expressed as the percentage of farmers that actually achieve expected yields after applying the DST-enabled fertilizer recommendations received from EAs. We include five levels ranging from less than 31% to more than 90%. The fourth attribute 'delivery platform' relates to the format or platform in which extension recommendations are delivered. This is defined by three levels: non-mobile platforms (desktops/laptops), quick guides (paper-based) and mobile platforms (smartphones/tablets). The fifth attribute 'delivery language' relates to the operating language of the tool and the recommendation output. The levels are: English only, native only and both English and native. The sixth attribute 'time cost' describes the amount of time needed for an EA to generate a fertilizer recommendation with the DST. This attribute is defined by four levels, ranging from 15 to 60 minutes per farmer. These levels were chosen based on a possible range of time that some EAs expressed as acceptable during a meeting with the extension providers.

Table 1: Attributes and attribute levels used in the choice experiment

Attributes	Attribute levels
User-friendliness (interface ease-of-use)	Low, Moderate, High
Detailed output	Low, Moderate, High
Predictive power	< 31%, 31 – 50%, 51 – 70%, 71 – 90%, > 90%
Delivery platform	Non-mobile (desktops/laptops), Quick guides (paper-based version), Mobile (smartphones/tablets)
Delivery language	English only, Native only, English + native
Time cost	15, 30, 45, 60 minutes per recommendation

We use a D-efficient design, which minimizes the number of choice sets, compared to a full factorial design, and improves the efficiency of parameter estimates (Hensher et al., 2015). In the design, we use small positive or negative priors (0.001 and -0.001) of parameters to improve the efficiency of the design. Priors were derived from discussions with EAs and from a review of the literature on extension and DST. We use Ngene software to generate the design, resulting in 12 paired choice sets randomly blocked into two blocks of six choice sets (D-error = 0.058). From these choice sets, we constructed 12 laminated choice cards (an example is given in Figure 1) each consisting of two unlabeled hypothetical options of a nutrient management DST (options A and B) and an opt-out (option C). An opt-out option is included to avoid forcing the EAs to accept the use of a DST, which corresponds to the reality of holding unto the use of the current traditional extension methods (Hensher et al., 2015).

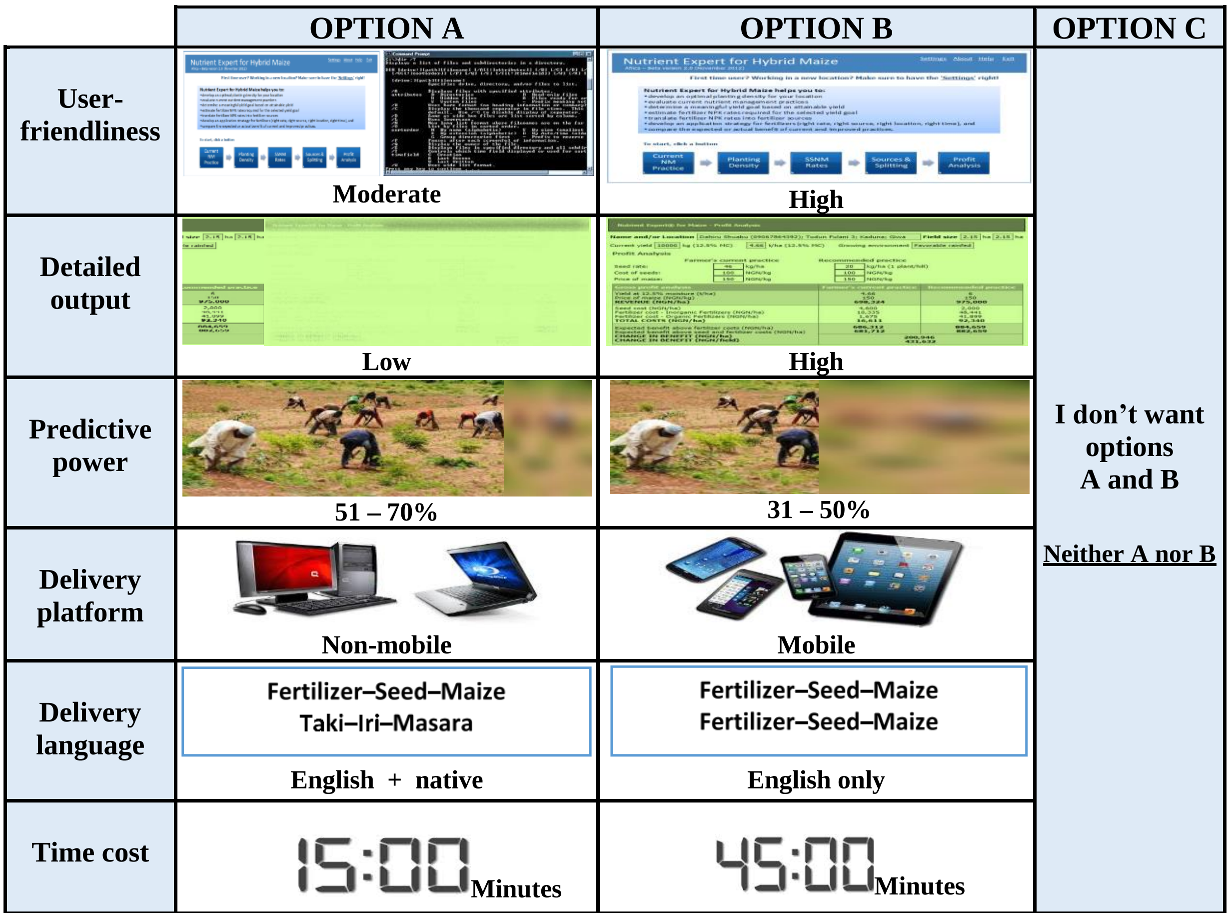

Figure 1. Example of a choice card used in the choice experiment

To implement the CE, we invited the public EAs to their respective zonal office and private EAs to the institutions they are affiliated to. We started with an introductory session in group to explain the purpose of the CE, the attributes and attribute levels and the hypothetical set-up. Cheap talk scripts were used to stress the need to give truthful responses and to minimize hypothetical bias (Cummings and Taylor, 1999). Subsequently, each EA separately was presented six choice cards in a random order by an enumerator, and was asked to choose the most preferred option. At the end, respondents were questioned about which attributes they ignored and about individual-specific and work-related characteristics.

3 Econometric Analysis

Analysis of CE data is based on random utility theory, in which the utility U_{ijs} of EA i of choosing alternative j among all alternatives in choice set s is given by an indirect utility consisting of a deterministic and a random component:

$$U_{ijs} = ASC + \sum_{k=1}^{6} \beta_i x_{ijs} + \varepsilon_{ijs} \quad i = 1, \dots, N;\ j = 1, \dots, J;\ s = 1, \dots, S \tag{1}$$

The vector of attributes x_{ijs} describes alternatives j with associated individual-specific parameters β_i. The idiosyncratic error term ε_{ijs} is assumed to be independently and identically distributed (iid). ASC is an alternative-specific constant to capture preferences for the opt-out option.

First, we estimate a mixed logit (MXL) model to account for preference heterogeneity across EAs (Train 2009). With the exception of time cost, all parameters are specified to be random with a normal distribution. The ASC is coded as 1 when the opt-out is chosen, 0 otherwise, which implies that a negative parameter for the ASC corresponds to a willingness to adopt DSTs. For ease of interpretation, all categorical variables are dummy-coded.

Second, we estimate two models to account for attribute non-attendance (ANA) – i.e. a situation where respondents ignore some attributes when making choices – which can be an important source of bias in the parameter estimates (Kragt, 2013; Alemu et al., 2013; Coffie et al., 2016). With stated ANA data, derived from the respondents at the end of the CE, we account for ANA in the MXL models by estimating a conventional ANA and a validation ANA model. The first implies constraining to zero those parameters for which respondents indicated to have ignored the attributes. The utility function can then be expressed as:

$$U_{ijs} = ASC + \sum_{k=1}^{6-\tau} \beta_i x_{ijs} + \varepsilon_{ijs} \tag{2}$$

where τ are attributes self-reported as ignored by some EAs. In the latter, two parameters are estimated for each attribute depending on whether the attribute is reported to be ignored or not by respondents (Alemu et al., 2013; Scarpa et al., 2013; Caputo et al., 2018; Oyinbo et al., 2019). This helps to validate the stated ANA responses and the conventional ANA model. The utility function is expressed as:

$$U_{ijs} = ASC + \sum_{k=1}^{6-\tau} \beta^1 x_{ijs} + \sum_{k=1}^{\tau} \beta^0 x_{ijs} + \varepsilon_{ijs} \tag{3}$$

where, the utility coefficients conditional on attendance are indicated with the superscript 1 (β^1) and those conditional on non-attendance with superscript 0 (β^0).

Third, we estimate a latent class model (LCM) to further unravel preference heterogeneity and explain the potential sources. An LCM assumes that a heterogeneous population of EAs consists of a discrete number of preference classes (latent classes) (Hensher et al., 2015). Preferences are assumed to be homogeneous within each latent class c but heterogeneous across classes. The probability of EA i choosing alternative j in choice set s is conditional on the EA's membership of latent class c, which is modeled using a multinomial logit specification:

$$Pr_{ijs}|c = \frac{\exp(\beta_c x_{ijs})}{\sum_{t=1}^{J} \exp(\beta_c x_{its})} \tag{4}$$

where β_c is the vector of class-specific parameter estimates. The choice and membership probabilities are jointly estimated (Boxall and Adamowicz, 2002). We estimate LCMs with two to five latent classes in order to sufficiently represent preference heterogeneity in our data. Selection of the optimal number of classes is based on the Akaike Information Criteria (AIC) and the Bayesian Information Criteria (BIC) (Boxall and Adamowicz, 2002). The individual-specific and work-related characteristics of EAs are compared across different latent classes to explain the possible sources of heterogeneity.

Fourth, to meaningfully compare the relative importance of the different attributes we need to take into account differences in scale (Greene and Hensher, 2003). To this end, we estimate marginal rates of substitution (MRS) between time cost and other attributes using Krinsky-Robb method with 2000 draws (Krinsky and Robb, 1986). The MRS is interpreted as the willingness to accept a higher time cost and by extension, more effort in the use of a DST for an increase in the utility of another attribute.

4 Results

Table 2 describes the individual- and work-related characteristics of the EA respondents, which are used to explain observed preference heterogeneity (as described later in this section).

Table 2: Summary statistics of extension agents' characteristics

Variables	Mean	Std. Dev.
Individual-specific characteristics		
Male EA (dummy)	0.95	0.35
Age of EA (years)	39.58	10.48
Married EA (dummy)	0.82	0.39
Education of EA (years)	18.88	1.82
Engage in agriculture (dummy)	0.88	0.32
Proficient in the use of a smartphone/tablet (dummy)	0.74	0.44
Own a smartphone (dummy)	0.44	0.50
Own a tablet (dummy)	0.02	0.15
Work-related characteristics		
Affiliated to public extension organization (dummy)	0.87	0.34
Extension experience (years)	12.74	10.27
ICT-based extension experience (dummy)	0.29	0.45
In-service training in last one year:		
Soil fertility-related (dummy)	0.72	0.45
ICT-related (dummy)	0.21	0.41
Access to transport facilities for extension purpose (dummy)	0.48	0.49
Receive adequate supervision (dummy)	0.95	0.22
Receive regular promotion (dummy)	0.83	0.38
Receive timely remuneration (dummy)	0.96	0.20
Perceive job to be secure (dummy)	0.93	0.25
% of working time devoted to soil fertility-related issues (%)	63.22	
Aware of site-specific nutrient management (dummy)	0.72	0.45
Farmers often request for soil fertility-related advice (dummy)	0.98	0.16
Observations	320	

Table 3 reports the results of the mixed logit (MXL) models, including the standard MXL without controlling for ANA, the conventional ANA and validation ANA models. Thirty three percent of the EAs reported to have ignored at least one attribute, which supports the estimation of ANA models. The estimated coefficients of the conventional ANA model are very close to those of the standard MXL model, which implies that results are robust to ANA. This is further corroborated by the results of the validation ANA model, that shows similar coefficients as in the MXL model for non-ignored attributes and coefficients that are not significantly different from zero - except for predictive power – for ignored attributes. We can conclude that the choice behavior of the EAs is consistent with their stated ANA information, and that MXL results are not biased (Scarpa et al., 2013; Caputo et al., 2018). We therefore base our discussion on the MXL results.

The ASC coefficient estimate is significantly negative, which indicates that the EAs generally prefer the use of DSTs for site-specific extension advice on nutrient management. This supports the ongoing efforts to develop such DSTs for maize in the research area. In general, the EAs prefer DSTs with a higher level of user-friendliness, more detailed output, and a higher predictive power. In addition, they prefer a mobile platform in the native or a combination of English and the native language. DSTs that have a higher time demand per output and paper-based DST platforms are disliked by the EAs. Standard deviations are significantly different from zero, except for the detailed output attribute. This indicates that there is heterogeneity in preferences across EAs.

Table 3: Results of mixed logit models, with and without control for attribute non-attendance (ANA)

	MXL		Conventional ANA		Validation ANA			
					Considered attributes		Ignored attributes	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
ASC	-2.57***	Fixed	-2.72***	Fixed	-2.58***	Fixed		
	(0.26)		(0.24)		(0.26)			
Time cost (minutes/output)	-0.01**	Fixed	-0.01***	Fixed	-0.01**	Fixed	-0.01	Fixed
	(0.00)		(0.00)		(0.00)		(0.01)	
User-friendliness: moderate	0.50***	0.66***	0.57***	0.61***	0.49***	0.66***	0.49	0.18
	(0.13)	(0.18)	(0.12)	(0.17)	(0.13)	(0.18)	(0.35)	(0.59)
User-friendliness: high	0.49***	-0.44**	0.55***	0.16	0.50***	0.24	0.26	0.46
	(0.12)	(0.22)	(0.11)	(0.51)	(0.12)	(0.39)	(0.37)	(0.62)
Detailed output: moderate	0.35***	0.37	0.27***	0.28	0.38***	0.37	-0.12	0.06
	(0.11)	(0.26)	(0.10)	(0.29)	(0.11)	(0.27)	(0.45)	(0.59)
Detailed output: high	0.29***	-0.03	0.29***	0.30	0.28**	0.31	0.61	0.70
	(0.11)	(0.91)	(0.10)	(0.26)	(0.11)	(0.28)	(0.50)	(0.71)
Predictive power	0.01***	-0.01***	0.01***	0.01**	0.01***	0.01**	0.01***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Platform: paper	-0.23**	0.76***	-0.19*	0.77***	-0.25**	0.85***	0.07	0.04
	(0.11)	(0.18)	(0.10)	(0.17)	(0.11)	(0.18)	(0.38)	(0.40)
Platform: mobile	0.43***	0.50***	0.38***	0.38**	0.42***	0.45**	0.55	0.72
	(0.10)	(0.19)	(0.09)	(0.21)	(0.10)	(0.21)	(0.37)	(0.49)
Language: native	0.20*	-0.38*	0.18*	0.16	0.21*	0.23	-0.23	0.61
	(0.11)	(0.20)	(0.10)	(0.30)	(0.11)	(0.30)	(0.37)	(0.52)
Language: English + native	0.38***	0.83***	0.29**	0.81***	0.40***	0.90***	-0.01	0.43
	(0.14)	(0.18)	(0.13)	(0.16)	(0.14)	(0.18)	(0.39)	(0.56)
N	5,760		5,760		5,760			
Log likelihood	-1350.33		-1358.97		-1339.99			
AIC	2740.65		2757.90		2758.00			
BIC	2873.83		2869.10		2974.80			

Notes: Asterisks ***, **, and * denote any variable significant at 1%, 5%, and 10% levels respectively.
Standard errors reported between parentheses.

Table 4 presents the results of a latent class model (LCM), which allows to further explore heterogeneity in preferences, and gain better insights on how the EAs trade off the attributes of DSTs. We selected a model with two latent classes based on a comparison of the information criteria across models with two up to five classes. Preference class one (PC1) includes 52% of the sampled EAs and preference class 2 (PC2) 48%. In both classes, EAs are in general willing to accept the use of DSTs, and have high preferences for DSTs that limit the time demand per recommendation output and that have a moderately to highly user-friendly interface. Yet, we observe substantial heterogeneity in preferences between the two classes for the other attributes. EAs of PC1 prefer DSTs with highly detailed output and a strong predictive power while EAs in PC2 are indifferent to these attributes. EAs of PC2 prefer DSTs on mobile devices – and dislike paper-based tools – and DSTs that use the native language or a combination of the native language and English while EAs in PC1 are indifferent to these attributes.

Table 4: Results of latent class models

	Preference class 1 = 52%		Preference class 2 = 48%	
	Coefficient	Std. error	Coefficient	Std. error
ASC	-2.15***	0.40	-3.66***	0.93
Time cost (minutes/output)	-0.01*	0.00	-0.01*	0.01
User-friendliness: moderate	0.39**	0.18	0.67***	0.25
User-friendliness: high	0.19	0.18	1.02***	0.31
Detailed output: moderate	0.26	0.18	0.35	0.25
Detailed output: high	0.45***	0.16	-0.12	0.28
Predictive power	0.01***	0.00	0.00	0.00
Platform: paper	0.21	0.19	-0.66*	0.35
Platform: mobile	0.15	0.15	0.59***	0.15
Language: native	0.15	0.16	0.46*	0.25
Language: English + native	-0.19	0.27	1.14**	0.56
N	5,760			
Log likelihood	-1344.04			
AIC	2734.07			
BIC	2887.22			

Notes: Asterisks ***, **, and * denote any variable significant at 1%, 5%, and 10% levels respectively.

To explore the sources of preference heterogeneity, we compare individual- and work-related characteristics of EAs between the two PCs (Table 5). The results show that PC2 EAs have a significantly higher education, a lower likelihood to engage in agriculture, and a higher likelihood to be proficient in the use of smartphones and/ or tablets, to have experience with ICT-based extension, to receive regular promotion and to be paid timely. This might explain their strong preferences for DSTs with mobile platforms. The differences in observed characteristics between the two PCs are significant but very small, which implies that unobservable characteristics, such as motivation and ability, likely play a role as well in determining preference heterogeneity.

Table 5: Profile of extension agents characteristics across latent preference classes

	Latent class 1		Latent class 2		
	Mean	Std. Dev.	Mean	Std. Dev.	Sig.
Individual-specific characteristics					
Male EA (dummy)	0.95		0.95		
Age of EA (years)	39.64	10.49	39.51	10.49	
Married EA (dummy)	0.79	0.41	0.85	0.36	
Education of EA (years)	18.71	1.88	19.06	1.73	*
Engage in agriculture (dummy)	0.91	0.29	0.85	0.36	*
Proficient in the use of a smartphone/tablet (dummy)	0.70	0.46	0.78	0.41	*
Own a smartphone (dummy)	0.40	0.49	0.48	0.50	
Own a tablet (dummy)	0.01	0.11	0.03	0.18	
Work-related characteristics					
Affiliated to public extension organization (dummy)	0.87	0.33	0.86	0.35	
Extension experience (years)	12.78	10.45	12.69	10.09	
ICT-based extension experience (dummy)	0.23	0.42	0.35	0.48	**
In-service training in last one year					
Soil fertility-related (dummy)	0.75	0.44	0.69	0.46	
ICT-related (dummy)	0.19	0.39	0.24	0.42	
Access to transport facilities for extension purpose (dummy)	0.49	0.50	0.46	0.50	
Receive adequate supervision (dummy)	0.95	0.23	0.95	0.22	
Receive regular promotion (dummy)	0.80	0.40	0.87	0.34	*
Receive timely remuneration (dummy)	0.93	0.25	0.98	0.14	**
Perceive job to be secured (dummy)	0.94	0.24	0.93	0.26	
% of working time devoted to soil fertility-related issues (%)	63.0		63.5		
Aware of site-specific nutrient management (dummy)	0.74	0.44	0.69	0.46	
Farmers often request for soil fertility-related advice	0.98	0.13	0.97	0.18	
Observations	167		153		

Notes: Two-sided t-tests of mean differences between EAs in latent class 1 and 2: asterisks ***, **, and * denote significant differences at 1%, 5%, and 10% levels respectively.

Table 6 reports the estimated MRS between time cost and other attributes. The MRS estimates show that in both classes EAs are willing to accept a higher time cost for a more user-friendly interface, but this trade-off is on average larger in PC2. In addition, EAs in PC1 are willing to accept a higher time cost for a more detailed and more accurate output while EAs in PC2 are willing to accept a higher time cost for a mobile delivery platform in the native language, or a combination of English and the native language.

Table 6: Marginal rate of substitution (MRS) between time cost and other attributes

	Preference class 1	Preference class 2
	Mean (95% confidence interval)	Mean (95% confidence interval)
User-friendliness: moderate	66.86 (-313.20 – 498.99)	74.31 (-203.49 – 360.52)
User-friendliness: high		113.42 (-193.98 – 465.70)
Detailed output: moderate		
Detailed output: high	78.84 (-254.35 – 489.48)	
Predictive power	1.45 (-7.20 – 10.55)	
Platform: paper		-73.51 (-295.43 – 91.49)
Platform: mobile		65.50 (-147.91 – 288.33)
Language: native		51.20 (-52.04 – 204.79)
Language: English + native		126.41 (-106.89 – 467.53)

Notes: MRS is only reported for significant coefficients in the latent class model in Table 4.

5 Discussion

We find that EAs in the maize belt of Nigeria are in general very willing to accept the use of DSTs for site-specific extension services on nutrient management for maize. While all EAs in the sample prefer DSTs with a more user-friendly interface that require less time to generate an output, we observe substantial preference heterogeneity for the other design features of DSTs, and identify two groups of EAs with a different preference pattern. The first group of EAs (52%) prefers DSTs that produce more accurate and more detailed output. This group can be described as 'more committed EAs', as EAs in this group care more about attributes related to the effectiveness of extension advice from a DST. This suggests that they are likely more driven by the underlying science or evidence-base aspects of DSTs over the practical features. The second group (48%) can be described as 'more pragmatic EAs' as these EAs are more keen about the practical attributes of DSTs such as the platform, the language and the user-friendliness of the interface. This suggests greater interest in the operational aspects of DSTs over the content-related attributes. Reflecting on the heterogeneous preferences of the two groups, the differences in observed characteristics between the two groups are very small and hence, unobservable characteristics, especially motivation, likely play an important role in explaining the differences in preferences.

Our finding that all EAs prefer DSTs with a user-friendly interface and a lower time requirement is consistent with Kragt and Llewellyn (2014), who report preferences for low time cost in a weed management DST in a developed country context. In addition, our results are in line with the extant literature on the design of user-friendly interfaces to stimulate the use of such tools (Bernet et al., 2001; Hochman and Carberry, 2011; Rose et al., 2016). Our finding of a strong preference by the 'more pragmatic EAs' for DSTs on mobile devices such smartphones and tablets contrasts with Kragt and Llewellyn (2014), who find that EAs prefer a spreadsheet-based platform. The result that some EAs prefer the use of native or a combination of native and English language is consistent with Tata and McNamara (2016), who opine that the use of local languages in the design of *farmbook*, an ICT-based extension tool, is more beneficial to farmers. This will likely facilitate better communication with the majority of farmers who do not understand English, and reduce the likelihood of misinterpreting the inputs and outputs of DSTs. Our findings on the strong preferences of EAs for DSTs that provide a more accurate and more detailed output are consistent with some studies that considered these attributes. For example, Kragt and Llewellyn (2014) find that a DST that generates more accurate output is strongly desired across the groups of EAs identified in their study, whereas we find this only to be the case for the 'more committed EAs'. Qualitatively, Hochman and Carberry (2011) find that the use of DSTs that allow for the provision of a wide range of options to farmers is keenly considered by tool users in a developed country setting. The fact that the sources of observed heterogeneous preferences in our study appear to derive from unobservable EA characteristics is consistent with Kragt and Llewellyn (2014) who find that observed demographic characteristics were not significant in explaining preferences.

Finally, we provide some specific policy implications of our findings. Our results imply that EAs in general are very willing to use DSTs, which supports the current interest and investments in site-specific and ICT-enabled extension tools. Our results imply that a user-friendly interface and a reduced time effort needed to generate extension advice are important to pay attention to in the design process of a DST. To stimulate uptake and facilitate better targeting, a more effective design will likely require DSTs to be differentiated along dimensions of its practical attributes such as the platform, language, etc., but not for attributes related to effectiveness. The latter should be non-negotiable and be strongly considered in the design stages of DSTs to allow for higher-quality agronomic advice to farmers. Yet, there are EAs who are indifferent to DSTs that can offer a more accurate and more detailed output and hence, will need to be better disposed to the quality of extension advice from a DST beyond the practical features. This may likely require improved capacity building for such EAs (Davis and Spielman, 2017; Makate and Makate, 2019).

6 Conclusion

In this paper, we analyze the preferences of extension agents (EAs) for the design of DSTs and their willingness to use such tools in the maize-based systems of northern Nigeria, where a new DST for nutrient management for maize, Nutrient Expert, has been piloted. We use data from a choice experiment (CE) and a survey among 320 EAs in the area. We find that the EAs are in general willing to use ICT-enabled DSTs for site-specific nutrient management advice to farmers, which lends credence to the transition to digital, and site-specific extension. All EAs prefer a DST with a more user-friendly interface that requires less time to generate an output. Yet, we find substantial preference heterogeneity for other features of DSTs, and identify two distinct groups of EAs. The first group of EAs, 'more committed EAs', are more keen about the effectiveness-related features of extension advice from DSTs. The second group includes the 'more pragmatic EAs', who are more interested in the practical features of DSTs. Overall, our results imply that there is high potential for the use of ICT-enabled DSTs for site-specific extension services in the study area. However, sustained uptake of such tools is more likely if DST design gives strong consideration to a more user-friendly interface, and lower time demand on EAs in the use of such DSTs. We note that while our study identifies user-friendliness as conceptually important, what this means in practice will require additional work (e.g. through co-development of interfaces, or AB testing of specific interface alternatives). Similarly, while the time required to generate a recommendation for a farm is identified as an important feature, more empirical work would be required to identify the specific amount of time that tool users find acceptable in a given context.

Our paper contributes to the sparse literature on the co-design of extension tools, and the use of CE among EAs. This should motivate further quantitative studies on perspectives of EAs and other stakeholders in the design of other extension tools particularly in SSA, where the design of DSTs is emerging. The use of CE method for such studies can generate useful *ex-*

ante insights to inform research, development and policy initiatives for the design of DSTs towards improving the efficiency of extension systems.

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