Role of knowledge in the adoption of new agricultural technologies: an approach and an application

M.A. Jabbar*, M.A. Mohamed Saleem and Solomon Gebreselassie

International Livestock Research Institute, PO Box 5689, Addis Ababa, Ethiopia
Fax: 251-1-464645 E-mail: M.Jabbar@cgiar.org
E-mail: ILRI-Ethiopia@cgiar.org
*Corresponding author

Hailu Beyene

Ethiopian Agricultural Research Organisation, PO Box 2003, Addis Ababa, Ethiopia
Fax: 251-1-611222 E-mail: IAR@telecom.net.et

Abstract: Empirical studies on agricultural technology adoption generally divide a population into adopters and nonadopters, and analyse the reasons for adoption or nonadoption at a point in time. In reality, technology adoption is not a one-off static decision, rather it involves a dynamic process in which information gathering, learning and experience play pivotal roles, particularly in the early stage of adoption. A conceptual framework for an adoption pathway is suggested in which farmers move from learning to adoption, to continuous or discontinuous use over time. The framework was applied to understand the adoption pathways for vertisol management technology in highland Ethiopia. Analysis of a sample of 585 households confirmed that a simple classification of farmers as adopters and nonadopters was inadequate to understand the adoption process. Rather a multistage decision process in which farmers moved from learning to adoption to continuous or discontinuous use was more appropriate. The sets of factors that significantly influenced decisions to acquire knowledge about BBM, to adopt and then to use it continuously or discontinuously were different. The lag between learning and adoption, and the possibility of discontinuation and readoption imply that a longer period will require for majority of the farmers to use the technology than if adoption was a one off decision leading to continuous use.

Keywords: adoption; adoption pathways; Africa; Ethiopia; innovations; knowledge; logit; technology; tobit; versitols.

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Biographical notes: Mohammad Jabbar is an Agricultural Economist with the International Livestock Research Institute, Addis Ababa, Ethiopia. He has a PhD in agricultural economics from the University of Wales, UK and a Masters from Bangladesh Agricultural University, Mymensingh. He has over 30 years of teaching, research, consulting and policy advising experiences in Asia and sub-Saharan Africa. His research interests include technology assessment and adoption, systems oriented participatory research approaches, marketing, market innovations and policies, and natural resources management policies.

M.A. Mohamed Saleem is an Environmental Agronomist with a PhD from the University of Ibadan, Nigeria. He has over 30 years of teaching, research and research management experiences in sub-Saharan Africa. He was a senior scientist with the International Livestock Centre for Africa, and for several years conducted research on feed and forage technologies for smallholder farms in West Africa. Later he was Leader of the Highlands research programme of the International Livestock Research Institute in Addis Ababa, Ethiopia, and led ILRI's global research in the highlands of Africa and Asia, especially with a focus on sustainable agriculture and natural resources management. He retired from ILRI in 2001 and is currently a freelance consultant.

Solomon Gebreselassie is an Agricultural Economist with a Masters from Alemaya University, Ethiopia. He was an extension specialist in the Ethiopian Ministry of Agriculture for some years, then joined ILRI as a research technologist. He is engaged in farming systems and participatory technology development and assessment research.

Hailu Beyene is an Agricultural Economist with the Ethiopian Agricultural Research Organisation, Addis Ababa, Ethiopia. He has a Masters from the University of the Philippines at Los Banos and is currently finishing his PhD at the University of Pretoria, South Africa. He has many years of experience in farming systems research, economic assessment of technologies and adoption analysis.

1 Introduction

In the literature on technology adoption, a distinction is made between diffusion and adoption. Diffusion is considered to begin at a point in time when an innovation is ready for use, and the main focus of diffusion is to explain how the innovation or technology is made available to the potential users. The earliest users of the technology may be called innovators and the diffusion process involves the spread of the innovation to the rest of the population. On the other hand, adoption studies consider the behaviour of individuals in relation to the use of the technology, particularly the reasons for adoption at a point in time, or the reasons for time of adoption for individual users, are of primary interest. Relative to adoption, diffusion may be viewed as a dynamic process over time. Inter-farm or inter-sectoral diffusion curves may be derived by aggregating the frequency distribution of adopters arranged on a time scale [1–3].

Empirical studies on agricultural technology adoption generally divide a population into adopters and nonadopters (potential adopters), and analyse the reasons for adoption or nonadoption at a point in time principally in terms of socio-economic characteristics of the adopters and nonadopters [3,4]. Based on evidence in consumer demand theory that demand for a product is significantly affected by the consumer's perceptions of the product's attributes [5,6], some recent adoption studies have included farmers' subjective assessment of technology attributes as explanatory variables [7–9].

In this paper, the deficiencies of these static approaches to analyse and predict the potential for adoption of a new technology, particularly at the early stage of diffusion, are discussed. Then an alternative approach is suggested in which information gathering, learning and experience play pivotal roles. At a given point in time, the decision to adopt, reject or defer decision is postulated to be influenced by the belief derived from the knowledge and perception about the technology at that point in time. The prior belief of a point in time may be later modified on the basis of new knowledge and/or observed performance, and a new decision about adoption may be taken. The characteristics of both the user and the technology are considered important in explaining adoption behaviour and the pathway for adoption. The resultant pathway for adoption has implications for the time frame and the volume of potential impact of a new technology. The approach is then tested with vertisol technology adoption in Ethiopia. The principal component of the technology is an animal drawn equipment for making broadbeds to avoid waterlogging during heavy rains so that improved wheat seeds can be sown early to allow optimum growing period for better yield. Traditionally waterlogging delays sowing leading to a shorter growing period and lower yield.

2 Adoption pathways: a conceptual framework

The logistic frequency distribution and its corresponding logistic curve (Figure 1) depict the conventional adoption pathway for a new technology. If N is the population of potential adopters of a new technology, the number of new adopters in period t is:

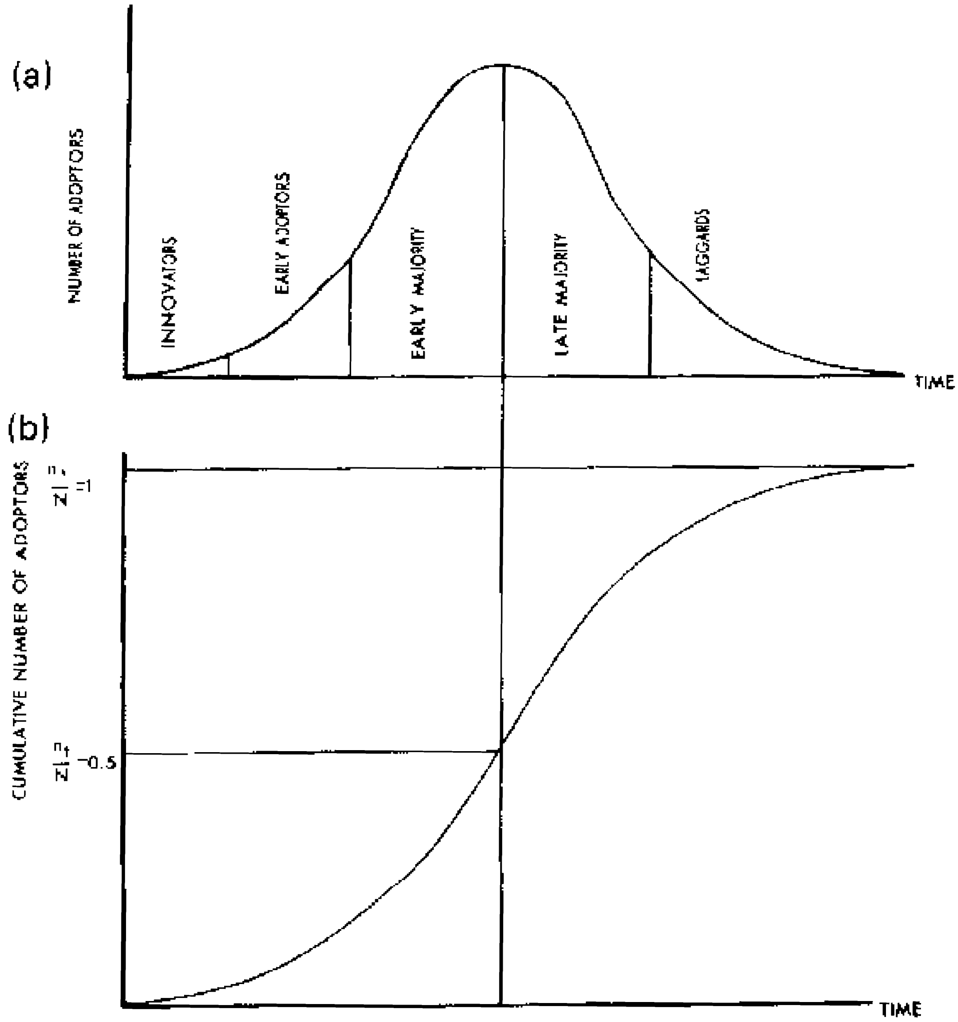
$$\frac{dn_t}{dt} = \beta \frac{n_t}{N}(N - n_t) \tag{1}$$

where β measures the speed of diffusion. Equation 1 may be solved for the frequency distribution of adoption over time as:

$$n_t = N\left(1 + e^{-\alpha - \beta_t}\right)^{-1} \tag{2}$$

where α is the constant of integration, that positions the distribution curve on the time axis. Equation 2 is the cumulative density function of the logistic frequency distribution and for constant β, it gives a bell-shaped frequency distribution for numbers adopting over time (Figure 1a). Equation 2 also gives sigmoid (S-shaped) logistic curve (Figure 1b), which is symmetric around the inflection point occurring at time $-(\alpha/\beta)$ corresponding to 50% adoption, and approaches zero and N asymptotically, as t tends to minus and plus infinity respectively (for details see for e.g., [10].

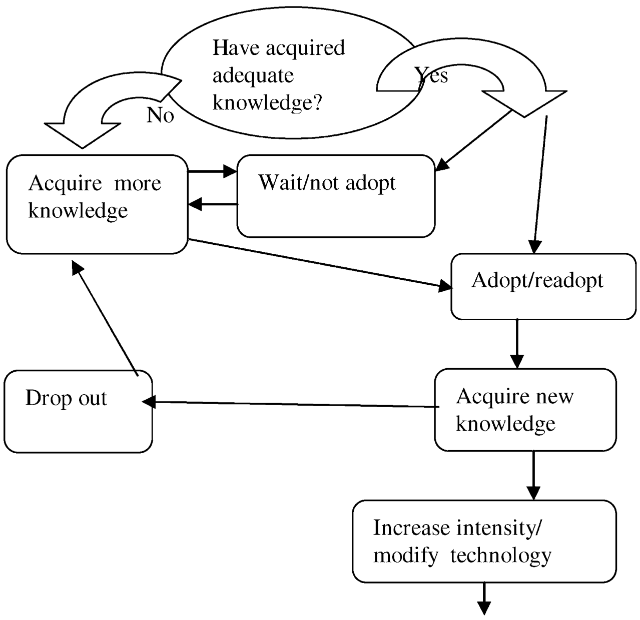
Figure 1 (a) Adopter categorisation. (b) The logistic curve



In models of this nature, at a point in time a population is divided into two groups, adopters and potential adopters, and it is implicitly assumed that the entire population or a certain ceiling level of the population eventually adopts the innovation and that, once adopted, the innovation is never rejected [3]. In some models, a population is divided into adopters, rejecters, disapprovers, and the remainder who are as yet uncommitted; the implicit assumption here is that once rejected or disapproved, the technology is never adopted again [11]. In reality, neither 'never rejected' nor 'for ever rejected' is a realistic assumption for most agricultural technology adoption process. Most agricultural innovations evolve as they diffuse because an innovation may be changed or modified by a user in the process of its adoption and use. When farmers are not involved in the technology generation process, awareness and knowledge about a new technology precedes any adoption decision. Information gathering and updating information through learning-by-doing and observation play important roles in the adoption process and there may be a lag between the time when farmers first hear about an innovation and the time they adopt it (e.g. [4,12]). However, empirical verification of the linkage between learning and adoption and what factors influence such linkage is rare. Saha et al. [13] have developed and tested a model in which producers' knowledge about a new technology (Phase I) determine the decision to adopt (Phase II) which in turn determine the intensity of adoption (Phase III).

Learning about and adoption of a technology may actually involve more complex processes (Figure 2).

Figure 2 Learning and adoption pathways for a new technology



Source: Jabbar et al. [14]

Any adoption decision is preceded by a period of awareness and learning. Initially, only limited amounts of information may be available or only a limited amount of available information may be digested. The optimal level of information is reached when information acquired over a period of time reaches a threshold level at which a decision on adoption can be made. Following Saha et al. [13], a producer's optimal information level may be considered as the outcome of an underlying utility maximisation problem:

$$i^* \equiv i(S) \tag{3}$$

where i* denotes the optimum level of information and S is a vector of related producer characteristics. A producer is considered to *know* about the new technology if

$$i^*(S) > i^o \tag{4}$$

where i^o is the threshold level of information at which a decision about adoption can be made. On the basis of knowledge at a point in time, a perception or belief about the technology is developed and a decision to adopt or reject or defer decision may be taken. The subsequent decisions may follow two pathways. In the first pathway, a decision to adopt is followed by a decision about the intensity or extent of adoption (in practice, these two decisions may be initially taken simultaneously). New knowledge and experience is gathered from learning-by-doing as well as observing other adopters, and a decision is made to increase intensity and/or modify the technology, or to discontinue the use of the technology. After acquiring more knowledge, a decision to readopt or defer adoption is taken. The process continues until a more stable decision is taken. In the second pathway, the initial perception or belief is modified on the basis of new knowledge and/or observed performance of adopters, and a new decision about adoption is taken. A decision to adopt takes the farmer along the pathway described above. A decision to reject or defer the decision will keep the farmer within the second pathway, whereby a new decision is taken after acquiring more knowledge [15]. Thus, the 'innovation assessment lag', defined as the time required between initial awareness and actual use of a technology, may vary depending on the farmer's access to knowledge, ability to decode that knowledge and formulate decision [12]. The lag is very short for innovators and very long for laggards.

The possibilities of permanent discontinuation or temporary discontinuation and readoption imply that a distinction need to be made between 'the number of new adopters' (Equation 1) and 'the number of net new adopters' in period t; the latter being defined as

$$\frac{dn_{nt}}{dt} = \beta \frac{n_{nt}}{N}(N - n_{nt}) \tag{5}$$

where $n_{nt} = n_t - n_{ot} + n_{rt}$ is net new adopter in period t, n_t is the number of new adopters in period t, n_{ot} is the number dropped out in period t and n_{rt} is the number readopted in period t. It is obvious that the frequency distribution of net new adopters, n_{nt}, over time is likely to give a bell-shaped curve only if $n_{ot} = n_{rt}$. If $n_{ot} > n_{rt}$, i.e. the number of drop-outs is greater than the number of readopters, the density function may not be bell-shaped, but the shape of the logistic curve may be bell-shaped rather than S-shaped, i.e. as t tends to ∞, n_{nt} tends to zero. Equations 1 and 5 have different implications about the time frame and volume of the potential impact of a new technology as the situation under Equation 5 implies a much longer period will elapse before a majority of the potential adopters will adopt and use the technology in a sustained manner. They also have important practical implication for farmers and extension agencies. It is therefore necessary to understand the possible pathways for adoption of a new technology and the associated factors, and take corrective measures, e.g. take more positive steps for diffusion of information for increasing awareness, remove supply constraints, to facilitate rapid adoption.

3 The technology and data source

Out of about 12 million ha of vertisols in Ethiopia, only about 30% are used because these productive soils suffer from poor internal drainage and resultant waterlogging during the rainy season. The cultivated vertisols are ploughed before the main rains and sown towards the end of the rainy season to avoid waterlogging, so the fields are exposed to soil erosion and crops grow on residual moisture giving low yields. In order to better use vertisols by improving drainage, the Joint Vertisols Project (JVP), a research consortium consisting of the Ethiopian Agricultural Research Organisation, The Ministry of Agriculture, the International Livestock Research Institute and the International Crops Research Institute for the Semi-arid Tropics, developed a broadbed maker (BBM), an equipment made by joining two local ploughs called *Mareshas*. The BBM is operated by a pair of oxen to create two furrows on two sides of a 1.5-m bed. During heavy rains, the furrows allow excess water from the bed to be expelled to a sub-field or main drain at the end of the plot. Better drainage allows early sowing, longer growing period and higher yields. A suitable agronomic package (crop varieties, planting dates, and fertiliser regime) to complement the BBM has been developed [16].

After on-station trials, the BBM package was tested by JVP on a few farms at five vertisol sites during 1986–1989 to test its technical performance. The results led to modification of some components of the package. During 1990–1995, on-farm research was continued in three (Inewari, Hidi, Ginchi) of the five sites, with a particular focus on the adoption behaviour of farmers. In the three sites, out of a total of 1553 households, 598 (28%) used the technology at least in 1 year during 1989–1995. Since the technology was accessible to any farmer in the study communities who wanted to use it, the adopters could be assumed to be randomly distributed. Of these, full information on farm characteristics and other profiles were available for 474 households from adopter monitoring forms of the JVP. For the remaining 124, one or more important piece of information was missing. Therefore, for the purposes of this analysis, data from the 474 adopters were used along with a random sample of 120 nonadopters (40 from each of the three sites) to determine factors influencing the adoption behaviour of these farmers over the period 1990–1995. Data for the nonadopters were collected by JVP staff during 1995–1996 on a recall basis.

The sample farms produce various crops, principally teff, wheat and pulses, and raise cattle and sheep. In Inewari, where rainfall is high and the waterlogging problem is also more intense than the other two areas, farmers make broadbeds after primary tillage using women and child labour to minimise waterlogging for early planting of wheat. Therefore, for them a better technology like the BBM that can save women and children from drudgery was expected to be attractive. In the other two areas, farmers practice late planting to avoid waterlogging, so for them the BBM is a new technology for early planting. These differences are expected to influence the adoption pattern of BBM. The findings from this analysis will be useful for understanding the adoption pathways for the BBM package and its implication for impact in the wider community, as an increasing number of BBMs are being distributed to farmers by extension and development agencies.

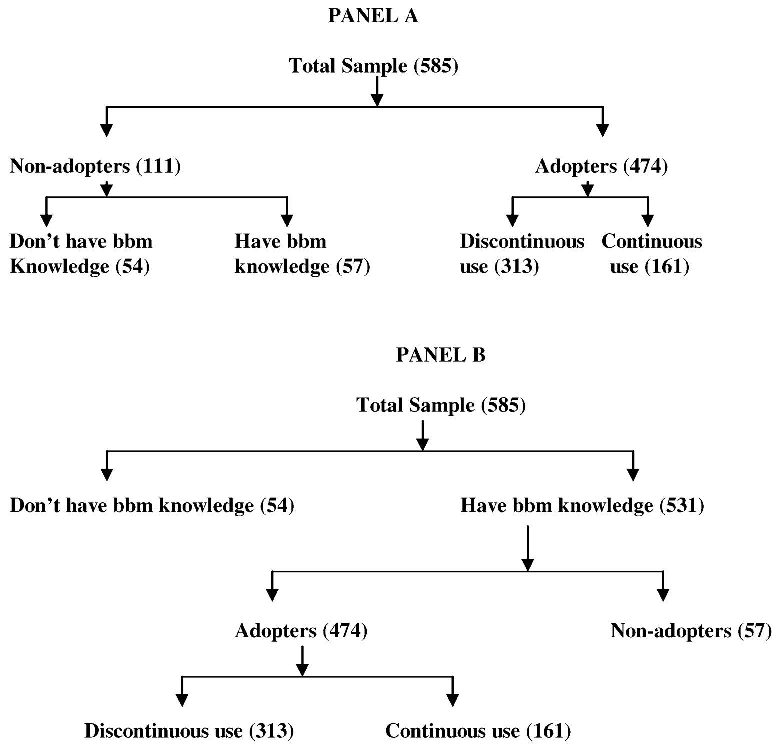
4 Results and discussion

4.1 Farm types

The farms in the sample had gone through the complex pathways of learning and adoption depicted in Figure 2 but a full account of the process could not be captured from the monitoring forms and the survey. Also, a fully dynamic model could not be constructed to empirically test the entire complexity of the process. Instead, the pathway was simplified by identifying three discrete steps in the process of learning and adoption: whether farms had acquired knowledge about BBM, whether farms had adopted BBM, and once adopted whether BBM was used continuously or discontinuously. In the conceptual framework it was argued that a producer is considered to 'know' about a new technology if his/her acquired information reaches a threshold level to permit decision making on adoption. In the present study, the threshold level of information was not directly observable, so a farmer was considered to have knowledge about BBM if he/she heard about BBM and its functions and/or saw it functioning either on a neighbour's farm or at the test plot of the JVP. A farmer was considered as an adopter if he/she used the technology at least once during 1990–1995. A farmer was considered a continuous user if, after adoption, the use was not discontinued within the study period.

Factors influencing these decisions were then identified . This was different than the conventional classification of farms into adopters and nonadopters. Figure 3 shows the distribution of the sample households according to the conventional and the proposed modified classification. According to the conventional approach (Panel A), out of 585 sample households, 111 were nonadopters and 474 were adopters. Among the nonadopters, 54 had not acquired sufficient knowledge about BBM and 57 had, but did not decide to adopt yet. Among the 474 adopters, 313 used the technology discontinuously and 161 continuously. It was argued earlier that acquisition of knowledge and information precedes any decision to adopt. So in Panel B, 585 households were first divided into those who had not yet acquired knowledge about BBM (54) and those who had (531); among those having knowledge, 57 did not adopt yet and 474 adopted; among the adopters, continuous and discontinuous use was the same as that in Panel A. So Panel A does not correctly depict the sequence of learning and adoption. Panel B shows a more appropriate sequence: farmers move from learning to adoption to continuous or discontinuous use.

Figure 3 Distribution of sample households according to BBM knowledge, adoption and use pattern in three research sites



4.2 Factors affecting BBM knowledge, adoption and use pattern: logistic regression analysis

Since farms were classified according to having or not having BBM knowledge, adopting or not adopting BBM, and using BBM continuously or discontinuously, each of these was defined as a binary dependent variable. Then, a multivariate logistic regression model that directly estimates the probability of an event occurring or not occurring, was used [17]. Equations were estimated to identify factors influencing farmers' probability of acquisition of BBM knowledge, probability of adoption of BBM, and probability of continuous use of BBM on the basis of classification Panels A and B, to compare which classification method gave better fit or explanatory power. Variables considered in these models are: age (of household heads in years), education (primary or over = 1, below primary or none = 0), BBMtraining (attended any BBM skill training session = 1, none = 0), cropland (ha), vertisol (ha under vertisol), waterlogged (ha with major waterlogging problem), familysize (no of persons), distance (km from the household to the nearest market), workanimal (no of work animals), BBMproblem (experienced problem with BBM = 1, not experienced = 0), credit (years had access to credit for BBM package), extrayield (expected extra yield (kg/ha) from crop produced with BBM compared to one replaced by BBM).

Percent correct predictions from the best-fit models show that the predictive power of the equations are significantly higher for the sequential classification in Panel B than in Panel A. For example, when the entire sample is divided into adopter and nonadopter (Panel A), characteristics of 81% of the cases can be correctly predicted. When only those who have knowledge about BBM are divided into adopters and nonadopters (Panel B), 92% cases can be predicted correctly. Similarly, when only nonadopters are divided into those having and not having BBM knowledge (Panel A), 78% of cases can be predicted correctly compared to 91% when the entire sample is first divided into those having or not having BBM knowledge (Panel B). So Panel B was used for further analysis and interpretation.

Estimated coefficients and related statistics for the best fit equations show that the models correctly predicted 91% cases in terms of BBM knowledge, 92% cases in terms of BBM adoption and 78% cases in terms BBM use pattern (Table 1).

Table 1 Estimated coefficients of logistic regressions on BBM knowledge, BBM adoption and BBM use pattern

	Dependent variables					
Variables	*BBM knowledge* $\beta(\mathrm{Exp}(\beta))$		*BBM adoption* $\beta(\mathrm{Exp}(\beta))$		*BBM use pattern* $\beta(\mathrm{Exp}(\beta))$	
Location						
Inewari	0.0		0.0		0.0	
Hidi	−0.468	(0.626)	4.027	(55.82)	−0.599	(0.550)
Ginchi	−2.114	(0.121)	−1.117	(0.327)	−3.465	(0.031)
Education	−0.345	(0.708)	−1.226	(0.294)	0.411	(1.508)
BBMtraining	–		3.128	(22.83)	−0.027	(0.973)
Age	−0.021	(0.979)	0.006	(1.005)	0.010	(1.010)
Cropland	0.219	(1.245)	0.440	(1.551)	−0.057	(0.945)
Vertisol	1.514	(4.543)	−0.042	(0.894)	0.226	(1.253)
Waterlogged	0.004	(1.004)	0.775	(2.170)	0.258	(1.295)
Familysize	−0.135	(0.874)	0.123	(1.134)	0.006	(1.009)
Distance	−0.136	(0.873)	−0.300	(0.741)	0.025	(1.030)
Workanimal	0.479	(1.615)	−0.392	(0.676)	0.122	(1.130)
BBMproblem	–		–		0.437	(1.545)
Extrayield	–		–		0.006	(1.001)
Credit	–		–		0.892	(2.440)
Constant	2.612		3.022		−5.058	
−2 Log Likelihood	303.320		189.783		423.609	
Goodness of fit	535.667		393.364		443.554	
% correct prediction	90.9		92.2		78.0	

Notes: Codes for dependent variables: BBM Knowledge: yes = 1 no = 0; BBM adoption: yes = 1 no = 0; BBM use pattern: continuous = 1 discontinuous = 0

The figures in the parentheses are expected values of βs. If β_i is positive, $\mathrm{E}(\beta_i) > 1$, which means that the odds of change in the dependent variable are increased when the ith independent variable increases by one unit. If β_i is negative, $\mathrm{E}(\beta_i) < 1$ which means that the odds are decreased. If $\beta_i = 0$, $\mathrm{E}(\beta_i) = 1$ which leaves the odds unchanged. The absolute values of $\mathrm{E}(\beta)$) indicate the factor by which the odds change (for more details see [17]).

In general, there were significant differences between the three sites in terms of BBM knowledge, adoption and use pattern. In general, compared to Inewari, a farmer located in Hidi or Ginchi was less likely to have acquired BBM knowledge. Among those who had BBM knowledge, a farmer located in Hidi was many times more likely to have adopted BBM, while a farmer in Ginchi was significantly less likely to have adopted BBM. Among adopters, a farmer located in Hidi or Ginchi was significantly less likely to have used the package continuously. The discontinuous use was more pronounced in Ginchi.

These differences might be because farmers in Inewari use handmade broadbeds, so they probably were generally more eager to learn about a better substitute and use it. Also the farmer-to-farmer training programme practiced in Inewari in 1993 gave Inewari farmers a better opportunity to learn compared to the other two locations. Inewari and Hidi farmers also had more regular access to credit compared to those in Ginchi. Some of the other factors, or their interactions, which might have influenced differences in BBM knowledge, adoption and use pattern among the three sites are size of land ownership, extent of vertisol and waterlogging problem, animal ownership and education. Average cropland per farm was 1.45 ha in Inewari, 1.75 ha in Hidi and 2.95 ha in Ginchi. vertisols constituted 49% of cropland in Inewari, 51% in Hidi and 91% in Ginchi. However, only 19% of cropland in Inewari and 17% in Hidi faced major waterlogging problems compared to 42% in Ginchi. Farmers in Inewari owned 1.66 work animals per farm compared to 2.21 in Hidi and 2.17 in Ginchi. Fifty nine percent of the household heads in Inewari and 61% in Ginchi had primary or higher level education compared to 38% in Hidi.

Among other factors, education, area of cropland, area of cropland under vertisol, number of work animals, family size and distance from market had significant influence on whether a farmer has acquired BBM knowledge or not. Household heads with better education (primary level or over) were less likely to know about BBM than those with no formal education. Households with a larger cropland area and area under vertisol and a larger number of work animals were more likely to have acquired BBM knowledge. Among these, the area under vertisol had the most dramatic effect on the odds of a farmer being knowledgeable about BBM: with one unit increase in the area under vertisol, the odds of a farmer knowing about BBM increased 4.5 times. Since BBM is specifically meant to address the problem of vertisol, a high degree of influence of this variable on farmers' willingness to learn about BBM is normally expected. The positive effect of the number of work animals on the acquisition of BBM knowledge might be explained by the fact that a pair of animals was required to pull the BBM, so farmers with two or more animals were perhaps more interested to know about the BBM than those having no or only one animal.

Larger family size decreased the odds of learning about BBM to some extent, perhaps because a larger family labour supply decreased the need for alternative technology. Greater distance from market also decreased the odds of learning about BBM, perhaps because the transaction costs of acquiring knowledge increased with distance and also information to distant parts of the research areas might have trickled down slowly.

Among those having knowledge about BBM, location, education, BBM training, cropland area, area with major waterlogging problem, distance to market and work animal ownership had significant influence on whether BBM has been adopted or not. The odds of adoption decreased as the level of education increased, while skill training in BBM increased the odds of adoption several times. Some adopters actually did not initially acquire the skill to operate the BBM, they hired somebody else to operate it. A typical example would be a farmer without BBM operational skill and another farmer with skill joining together with their *mareshas* to make the BBM.

Farmers with larger cropland areas and a larger area with major waterlogging problems were more likely to have adopted BBM. Although an area under vertisol significantly increased the odds of a farmer acquiring knowledge about BBM, it had no influence on adoption. Instead an area with a major waterlogging problem significantly increased the odds of adoption. In the sample sites, 60% of the cropland was under vertisol, nearly 50% of the cropland had some waterlogging problem, but only 23% of the cropland suffered from a heavy waterlogging problem that would benefit from BBM-type technology.

A greater distance to market decreased the odds of adoption, perhaps because distance adds to costs of a new technology and reduces the potential net benefits. Ownership of a larger number of work animals also decreased the odds of adoption, a characteristic rather difficult to explain, except that work animal ownership and cropland are highly correlated and cropland has a strong positive influence on adoption.

Among those who adopted the BBM package, the area under vertisol, area with a major waterlogging problem, perception about the problem with BBM technology and access to credit had a significant influence on whether BBM was used continuously or discontinuously. A higher level of education increased the odds of continuous use, but BBM training had no influence on use pattern. Both areas under vertisol and areas with major waterlogging problems increased the odds of using BBM continuously, which would be expected. The odds of continuous use was higher for farmers who perceived that the BBM had some problems or disadvantages compared to those who did not perceive such problem. This was an apparently unexpected result but could be explained by the fact that those who used continuously and for a longer period also were more likely to have experienced or detected problems of the BBM. The most important problem reported by farmers was about the heaviness of the BBM unit. The other problem, mentioned by a few, was the unsuitability of the BBM for too wet soil.

Credit for the BBM package was not a relevant variable in the equation explaining BBM knowledge, because credit was accessible only to those who knew about the BBM and had decided to adopt. Also credit was not used as a variable in the equation explaining adoption as all adopters had access to credit at least once. However, once adopted, a longer duration of access to credit for the BBM package significantly increased the odds of continuous use of the technology.

The expected extra yield from BBM use had no significant influence on BBM use pattern, although higher extra yield would be normally expected to induce continuous use. A possible reason is that, both within and between sites, there was wide variation in expected extra yield. The extent of higher yield expected from improved wheat, compared to the traditional crop (local wheat or teff) the BBM package would replace, was 418 ± 13 kg for the three sites (441 ± 19 kg for Inewari, 365 ± 20 kg for Hidi and 441 ± 30 kg for Ginchi).

4.3 Factors affecting adoption and duration of BBM use: tobit regression analysis

In the logistic regression model 2 (Table 1), adoption was considered a binary dependent variable, and factors influencing the probability of adoption were identified. Since adopters used the technology for different actual durations, in order to simultaneously identify the factors influencing adoption and the duration of use of BBM, adoption was defined as a truncated continuous variable in which nonadopters had a zero period of use and adopters had varying periods of use. Then tobit regression of the following form was used:

$$Y_i = \beta' X_i + u_i \tag{6}$$

where Y is a continuous truncated variable, X is a set of independent variables, β is a vector of parameters including a constant to be estimated, u is an error term, and both Y and u have normal distributions, actually truncated normal distributions. The parameters are estimated by maximum log-likelihood iteration. The parameters do not measure marginal effects of independent variables, they only show if any regressor has a significant influence on the regress (for general properties of the tobit model see [18–20]).

Two estimators were used in the empirical estimation of Equation 6 by employing the tobit procedure of LIMDEP software [21]. First, a full tobit model was used in which the entire sample of adopters and nonadopters were considered. In this case an estimated coefficient shows the joint effect of a regressor on both the probability of the dependent variable being non-zero, i.e. the probability of adoption of BBM, and the duration of use of BBM. Second, a truncated model was used in which only farms with non-zero adoption were considered. In this case, an estimated coefficient shows the effect of a regressor on the probability of a longer duration of use of BBM. The sample with non-zero adoption is a truncated part of a larger sample, hence truncated tobit rather than OLS estimator is appropriate to estimate coefficients [22].

The definitions of the independent variables used in both the models are those described earlier for the logistic model. The estimated coefficients of the full tobit model indicate that, compared to farmers in Inewari and Hidi, those in Ginchi had a significantly higher probability of adoption and longer period of use of BBM (Table 2). Among the three sites, sample farmers in Ginchi had the highest proportion of land under vertisols (91% compared to 49% in Inewari and 51% in Hidi) and the highest proportion of land with major waterlogging problems (42% compared to 19% in Inewari and 17% in Hidi). BBM training, area of cropland, number of work animals, and duration of access to credit had significant positive influences and family size had a significant negative influence on the probability of adoption and duration of use of BBM. All the positive effects are plausible; the negative effect of the family size may also be plausible if the larger labour supply from larger families reduced the need for BBM type technology for drainage.

Table 2 Maximum likelihood estimates for factors affecting adoption and the duration of use of BBM in three research sites

Independent variable	*Estimator*			
	Tobit		*Truncated*	
Constant	−0.413	(−2.678)	−1.369	(−5.822)
Location				
Inewari	0.000		0.000	
Hidi	−0.116	(−0.867)	−1.145	(−0.744)
Ginchi	0.377	(3.185)*	0.584	(3.345)*
Age	0.001	(0.257)	0.002	(0.526)
Cropland	0.127	(2.013)*	0.132	(1.434)
Vertisol	−0.061	(−1.002)	−0.080	(−0.881)
Waterlogged	0.035	(0.832)	−0.015	(0.255)
Familysize	−0.030	(−2.437)*	−0.039	(−2.087)*
Distance	0.030	(1.980)	0.031	(1.419)
Workanimal	0.066	(2.461)*	0.106	(2.632)*
BBMTraining	0.085	(2.775)*	0.104	(2.332)*
Education	0.016	(0.039)	0.019	(0.251)
BBMproblem	0.034	(0.500)	0.063	(0.594)
Extrayield	−0.001	(−1.876)	−0.001	(−0.569)
Credit	0.943	(40.144)*	1.119	(32.813)*
Log likelihood function	−347.749		−360.072	

Notes: Figures in the parenthesis are t-ratios
*indicate significant at less than 5% level

The estimated coefficients of the truncated model indicate that farmers in Ginchi had a higher probability of using BBM for longer periods. With the exception of the area of cropland, all the factors that significantly influenced the probability of adoption and duration of use also influenced, in the same manner, the probability of a longer period of use. Of all the variables, access to credit had the most significant influence on both the probability of adoption and the duration of use of BBM. Surprisingly, the area under vertisols and the area with major waterlogging problems had no significant influence on the probability of adoption and duration of use of BBM.

5 Conclusions

A conceptual framework for the adoption pathway is suggested, in which technology adoption is not a one-off static decision rather it involves a dynamic process in which information gathering, learning and experience play pivotal roles, particularly in the early stage of adoption. A decision to adopt, reject or defer the decision at a point in time is postulated to be influenced by the knowledge and perception acquired at that point in time. A new decision about adoption may be taken later after acquiring more knowledge and/or by observing the performance of those who had already adopted. The resultant pathways for adoption have further implications for the time frame and the potential impact of a new technology.

A simplified discrete formulation of the framework was applied to understand the adoption pathways for a vertisol management technology package, principally a piece of drainage equipment called broadbed maker (BBM), and related factors in three sites in highland Ethiopia. Analysis of a sample of 585 households showed that a simple classification of farmers as adopters and nonadopters was inadequate to understand the adoption process. Rather a multistage decision process, in which farmers move from learning to adoption to continuous or discontinuous use, was more appropriate. Application of logistic regressions to binary dependent variables BBM knowledge (yes vs no), BBM adoption (yes vs no), and BBM use pattern (continuous vs discontinuous) showed that the set of significant factors influencing these dependent variables were different. The lag between learning and adoption, and the possibility of discontinuation and readoption imply that a longer period will required for the majority of farmers to use the technology, than if adoption was a one-off decision leading to continuous use. For effective promotion of the package, extension and development agencies may benefit from using these indicators to identify and target potential adopters and also plan training and input supply programmes accordingly.

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References

1 Stoneman, P. (1983) *The Economic Analysis of Technological Change*, London: Oxford University Press.

2 Feder, G., Just, R.E. and Ziberman, D. (1985) 'Adoption of agricultural innovations in developing countries: a survey', *Economic Development and Cultural Change*, Vol. 33, pp.255–297.

3 Thirtle, C.G. and Ruttan, V.W. (1987) *The Role of Demand and Supply in the Generation and Diffusion of Technical Change*, London: Harwood Academic Publishers.

4 Feder, G. and Umali, D. (1993) 'The adoption of agricultural innovations: a review', *Technological Forecasting and Social Change*, Vol. 43, pp.215–239.

5 Jones, A.M. (1989) 'A. Double-hurdle model of cigarette consumption', *J. Appl. Econometrics*, Vol. 4, pp.23–29.

6 Lin, C.T.J. and Milon, J.W. (1993) 'Attribute and safety perceptions in a double-hurdle model of shellfish consumption', *Am. J. Agric. Econ.*, Vol. 75, pp.724–729.

7 Nowak, P. (1993) 'Why farmers adopt production technology', *Journal of Soil and Water Conservation*, Vol. 47, pp.14–16.

8 Adesina, A.A. and Zinnah, M.M. (1993) 'Technology characteristics, farmer perceptions and adoption decisions: a tobit model application in Sierra Leone', *Agric. Econ.*, Vol. 9, pp.297–311.

9 Adesina, A.A. and Baidu-Forson, J. (1995) 'Farmers' perceptions and adoption of new agricultural technology: evidence from analysis in Burkina Faso and Guinea, West Africa', *Agricultural Economics*, Vol. 13, pp.1–9.

10 Mahajan, V., Muller, E. and Bass, F.M. (1990) 'New product diffusion models in marketing: a review and directions for research', *Journal of Marketing*, Vol. 54, pp.1–26.

11 Sharif, M.N. and Kabir, C. (1976) 'System dynamics modelling for forecasting multilevel technological substitution', *Technological Forecasting and Social Change*, Vol.9, pp.89–112.

12 Fisher, A.J., Arnold, A.J. and Gibbs, M. (1996) 'Information and the speed of innovation adoption', *American Journal of Agricultural Economics*, Vol. 78, pp.1073–1081.

13 Saha, A., Love, H.A. and Schwart, R. (1994) 'Adoption of emerging technologies under output uncertainty', *American Journal of Agricultural Economics*, Vol. 76, pp.836–846.

14 Jabbar, M.A., Larbi, A. and Reynolds, L. (1996) 'Alley farming for improving small ruminant productivity in West Africa: ILRI's experiences', *Socio-economic and Policy Research Working Paper No 20*, International Livestock Research Institute, Addis Ababa, Ethiopia, p.96.

15 Jabbar, M.A., Beyene, H., Mohamed Saleem, M.A. and Gebreselassie, S. (1998) 'Adoption pathways for new agricultural technologies: an approach and an application to vertisol management technology in Ethiopia', *Socioeconomic and Policy Research Working Paper No 23*, International Livestock Research Institute, Addis Ababa, Ethiopia, p.27.

16 Mohamed Saleem, M.A. (1995) 'Fragile East African highlands: a development vision for smallholder farmers in the Ethiopian highlands', *Outlook on Agriculture*, Vol. 24, No. 2, pp.111–116.

17 Norusis, M.J. (1993) *SPSS for Windows: Advanced Statistics. Release 6*, Chicago, USA: SPSS Inc.

18 Tobin, J. (1958) 'Estimation of relationships with limited dependent variables', *Econometrica*, Vol. 26, pp.24–36.

19 McDonald, J.F. and Moffitt, R.A. (1980) 'The uses of tobit analysis', *Review of Economics and Statistics*, Vol. 62, No. 2, pp.318–321.

20 Kinsey, J. (1984) 'Probit and tobit analysis in consumer research', *Proceedings of the 30th Annual Conference of the American Council on Consumer Interests*, Atlanta, Georgia, April 11–14, p.7.

21 Anon. (1995) *LIMDEP. Version 7*, Econometric Software Inc. Bellport. USA.

22 Goetz, S.J. (1995) 'Markets, transaction costs and selectivity models in economic development', in G. J. Scott (Ed.) *Prices, Products and People: Analysing Agricultural Markets in Developing Countries*, London: Lynna Reinner Publishers.