What is technology adoption? Exploring the agricultural research value chain for smallholder farmers in Lao PDR.

Kim S Alexander, Garry Greenhalgh, Magnus Moglia, Manithaythip Thephavanh, Phonevilay Sinavong, Silva Larson, Tom Jovanovic, Peter Case

Abstract

A common and driving assumption in agricultural research is that the introduction of research trials, new practices and innovative technologies will result in technology adoption, and will subsequently generate benefits for farmers and other stakeholders. In Lao PDR, the potential benefits of introduced technologies have not been fully realised by beneficiaries. We report on an analysis of a survey of 735 smallholder farmers in Southern Lao PDR who were questioned about factors that influenced their decisions to adopt new technologies. In this study, we have constructed measures or states of adoption which identify key elements of an adoption decision-making nexus. Analysis was conducted to statistically group explanatory factors of adoption. The key explanatory factors represented attributes of the farmer, the factors considered when undertaking production decisions and elements of the agricultural value chain that present as opportunities or constraints. We describe the combination of farmer's personal attributes, perceptions of the value chain, and the introduction of new technologies by external actors as an "agricultural research value chain", where agricultural research activities intervene to derive greater benefits for local farmers. A generalised linear model, via Poisson (multiple) regression analysis on the identified explanatory factors, was applied to explore how they influence adoption measures and we found several significant relationships.

Keywords: measures of adoption; agricultural research value chain; adoption; Lao PDR; technologies

Abbreviations

Australian Centre for International Agricultural Research (ACIAR)
District Agriculture and Forestry Officers (DAFO)
Department of Technical Extension and Agro-Processing (DTEAP)
Integrated pest management (IPM)
Japan International Cooperation Agency (JICA)
Lao People's Democratic Republic (Lao PDR)
National Agriculture and Forestry Institute (NAFRI)
National University of Laos (NUoL)

Contact information

Kim S Alexander, kim.alexander56@gmail.com College of Business, Law and Governance, James Cook University, University Townsville Campus QLD 4811 Australia
Garry Greenhalgh, garry.greenhalgh8@gmail.com College of Business, Law and Governance, James Cook University Townsville Campus QLD 4811 Australia
Magnus Moglia, Magnus.Moglia@csiro.au Commonwealth Scientific and Industrial Research Organisation (CSIRO), Clayton South, Victoria, 3169 Australia
Manithaythip Thephavanh, thephavanh.mntt@gmail.com National Agricultural and Forestry Institute, Ban Nongviengkham, Xaythany District,Vientiane, Lao PDR

Phonevilay Sinavong, lanoysinavong@gmail.com National Agricultural and Forestry Institute, Ban Nongviengkham, Xaythany District,Vientiane, Lao PDR
Silva Larson, silva.larson@gmail.com College of Business, Law and Governance, James Cook University Townsville Campus QLD 4811 Australia
Tom Jovanovic, sonicentitytj@gmail.com College of Business, Law and Governance, James Cook University, Townsville Campus, QLD 4811 Australia.
Peter Case, peter.case@jcu.edu.au College of Business, Law and Governance, James Cook University, Townsville Campus, QLD 4811 Australia and University of the West of England (UWE), Bristol, United Kingdom

Author biographies

Dr Kim Alexander is an adjunct Senior Research Fellow at James Cook University. She has held social science research positions at CSIRO and the universities of Sydney, Melbourne, Wollongong and Charles Sturt. Her research experience over the last decade includes social aspects of agricultural change and rural and urban health and development in South East Asia. She has implemented projects that explore ecological and social vulnerability related to climate change, local water needs and access to water supplies, trans-boundary issues in the Mekong River Basin, health and wellbeing impacts of mining in southern Laos.

Dr Garry Greenhalgh has been an international consultant for over twenty years, primarily in FMCG, heavy process, general manufacturing and mining industries. His assignments have centred on business strategy and large-scale performance improvement for European and American companies in Europe (Benelux, Germany, Hungary), Russia, South East Asia (Indonesia, Vietnam, Malaysia, Thailand, Singapore) the Middle East (Saudi Arabia, Dubai, Oman), India, Pakistan, Australia, New Zealand, West Africa (Nigeria, Ghana) and China (Shanghai, Hong Kong). Prior to becoming a consultant Garry enjoyed a successful career in the food, paint and pharmaceutical industries, with senior line management positions in manufacturing and physical distribution. Garry's current work is with international development projects in S.E. Asia.

Dr Magnus Moglia is a CSIRO leader in systems and integration science who has been a staff member at the CSIRO since 2001. He arrived in Australia from Sweden in 2001 where he studied Physics and Applied Mathematics at the Royal Institute of Technology, as well as Civil Law, English, Statistics and Business Administration at Stockholm University. Whilst at CSIRO he has also completed a PhD in Environment from the Australian National University's Crawford School of Public Policy. He is an interdisciplinary systems scientist focusing on how to promote greater urban resilience. His current research explores two key enablers for urban change: a) using systems science to enable and promote technological solutions, b) using systems science for building capacity in cities for more holistic decision decision-making under uncertainty.

Ms. Manithaythip is currently undertaking a PhD at Adelaide University, South Australia. She is a graduate of the National University of Laos, and has a Master's degree in environmental science from Griffith University, QLD. She is has been involved in agricultural policy and climate change research and is a member of several important international, mulita-institutional agricultural projects at the National Agricultural Research Institution (NAFRI).

Dr Phonevilay Sinavong has a research position at the National Agriculture and Forestry Research Institute, Vientiane, Lao PDR. In 2015 Dr Sinavong was awarded a PhD in International Development from Nagoya University, Japan. Since then she has contributed to various international development projects with the Japan International Research Center for Agricultural Sciences (JIRCAS) and the Australian Centre for Internal Agricultural Research (ACIAR) and as a consultant a livelihood consultant, National Policy Facilitator and Project Coordinator of Pro-Poor Policy Approach for the Food and Agriculture Organization (FAO).

Dr Silva Larson is an Environmental and Social Impact Assessor with experience in major energy, mining and infrastructure projects. Her main interests are in the areas of stakeholder and community engagement; and planning and actions for livelihoods and wellbeing improvements. She specialises in development of programs and initiatives at regional and sectoral levels that lead towards decreased vulnerability and increased adaptive capacity to climate change.

Mr. Tom Jovanovic is an experienced GIS mapping specialist using ARCGIS, the most commonly and widespread used GIS computer mapping software. He had a long career at CSIRO and is now at the Australian National University, Fenner School of Environment & Society Canberra, Australia as a Visiting Fellow.

Professor Peter Case's research encompasses leadership studies, organizational development and international development. For the past six years he has been a programme management consultant for the Bill and Melinda Gates Foundation funded Malaria Elimination Initiative (MEI) at the University of California, San Francisco, advising on projects in the Greater Mekong Sub-region, Zimbabwe and Eswatini. He is leading a management development project for the MEI in southern Africa. He has extensive experience in leading rural development projects in Lao People's Democratic Republic and extensive experience managing executive development programmes internationally.

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Introduction

A common and driving assumption in agricultural research is that the introduction of research trials, new practices and innovative technologies[1] will result in technology adoption, and will subsequently generate benefits for farmers and other stakeholders (Cafer and Rikoon 2018). We denote this process as an inclusive *agricultural research value chain*, where agricultural research is aimed at providing valuable opportunities for

[1] Agricultural production and practices that differ from traditional practice, e.g., introduced technologies (new seed variety, new machinery, etc.) or new practices (changes to sowing times, changes to tillage practices, etc.)

local farmers. Inspired by the concept of Donut Economics (Raworth 2017, p. 31-60) to set more appropriate goals for the 21st century, we use the concept of the agricultural research value chain to mean:

> The process, in a holistic multi-actor sense, by which agricultural research provides value-achieving economic productivity goals and contributing to meeting the human rights of every person within the means of our life-giving planet.

Agricultural research activities, where demonstrated techniques lead to adoption and expanded areas of cultivation, have long been thought to improve household livelihoods, enhance food security and increase farm productivity (Hailu et al. 2014; IFAD and UNEP 2013; World Bank 2012). Technologies and innovations have traditionally been delivered to smallholder farmers through a technology-push of recommended agricultural practices and then have been expected to diffuse over time across social systems (FAO 2016; Food and Fertilizer Technology Center 2006; Theis et al. 2018). Often the rates of adoption have been disappointingly low and hence there has been a plethora of research dedicated to understanding adoption processes in varied agricultural contexts (Alcon et al. 2014; Feder et al. 1985; German et al. 2006; Hailu et al. 2014; Knowler and Bradshaw 2007; Pannell et al. 2006; World Bank 2012).

Many researchers have explored factors that may improve the chance of farmers' adoption of new technologies (Alexander et al. 2018; Ayele et al. 2012; Clarke et al. 2016; Gilles et al. 2013; Griliches 1957; Hogset 2005; Kebede 1992; Leeuwis and Van den Ban 2004; Marra et al. 2003; Pattanayak et al. 2003; Philip et al. 2019). However, we also know that technologies can be adopted in less prescribed terms, notably in terms of partial adoption, dis-adoption and re-adoption (Brown et al. 2017; CIMMYT Economics Program 1993; Cramb et al. 2015; Feder et al. 1985; Iwueke 1990; Jain et al. 2009; Jones 2005; Marra et al. 2003; Moser and Barrett 2002; Ndagi et al. 2016; Neill and Lee 2001; Sanders et al. 1996; Tegengne 2017). Adoption can also occur suddenly, due largely to changing circumstances, rather than through slow diffusion (Clarke et al. 2018).

In Lao PDR, the potential benefits of introduced technologies through the agricultural research value chain have not been fully realised by beneficiaries as, amongst other issues, farmers are generally limited by time, labour and resources (Cramb 2000; Manivong et al. 2014; Newby et al. 2011; Stür and Gray 2014). In our research with smallholder rice farmers in Southern Lao PDR, we found that the agricultural research value chain has a unique set of factors that are likely to impact on the chances of achieving eventual benefits for those involved in the adoption of new technologies (Moglia et al. 2018).

The research presented in this paper aims to illustrate our insights relevant to the agricultural research value chain, based on a survey of smallholder farmers in southern Lao PDR and associated statistical analysis, described in detail in a project report by Greenhalgh et al. (2017).

The article is structured as follows. We begin by illustrating the approaches used to evaluate adoption and the factors thought to influence smallholder farmers' propensity to adopt a new technology, as understood in relation to the agricultural research value chain. We subsequently explore the various forms of technology adoption and dis-adoption that have been raised in the literature. A household survey constructed from relevant research, is described and the results are discussed in terms of the factors known to influence adoption and the relevance to our measures of adoption as a function of the agricultural research value chain. Finally, we conclude by reflecting on the implications for adoption research studies and for Lao government agricultural policies.

Factors influencing the adoption of technology and innovation

Adoption has been defined as the decision to make full use of an innovation (a term used interchangeably with new technology) as the best course of action available, usually by going through a series of stages to adoption (Rogers 2003). From a sociological research perspective, individual adoption decisions are a result of the characteristics of potential adopters and ensuing perceptions surrounding innovation attributes, their adoption behaviours and the learning and communications involved in the various stages of innovation decision processes (Marra et al.2003). More specifically, the likelihood of adoption of agricultural technology is a function of the farmer's attributes, the attributes of the new technology and the surrounding context (Sattler and Nagel 2010). Schewe and Stuart (2015) showed that diverse production outcomes of dairy farmers in the USA were driven by farmers' individual values, goals, and personality traits. Reimer et al. (2012) showed that farmers were influenced by a complex array of attitudinal factors that drove adoption behaviours.

Following the sociological research perspective, economic research studies have focused on economic variables of adoption, initially through research on the uptake of hybrid corn varieties (Griliches 1957,1960). The economic perspective was extended by the studies of Mansfield (1961) looking into industrial innovations and by Rosenberg (1976) taking a business perspective. In addition, Lindner and Pardey (1979) introduced the importance of spatial diffusion of innovations and the role that infrastructure and/or supply aspects assume as possible variables. Interestingly, these economic, temporal and spatial diffusion models posit potential adopters as passive participants and they investigate the spread of knowledge about the innovation, rather than the rate of adoption of the innovation (Marra et al. 2003, Padel et al. 2015, Röling 2009, Scown 2019).

Feder et al. (1985) describe in detail many of the theoretical models that have traditionally been used to explore adoption. More recently, the adoption of innovative practices has been modelled by Eayrs (2016) using organizational change management models. Change agents, readiness for change, belief systems, desired outcomes, competing commitments and personal assumptions all play a role in changing sectorial practices and individual adoption of new practices as a function of the agricultural research value chain (Kotter 1996, 2011; Rafferty et al. 2013; Struckman and Yammarino 2003). In addition, Douthwaite et al. (2017) and Douthwaite and Hoffecker (2017) have taken a complex systems approach to the introduction of new technologies, where causal links between interventions and eventual impact are depicted and were found to be inherently uncertain and emergent.

Recently, Brown et al. (2017) developed a model to predict the adoption and diffusion of new ideas, practices and technologies in farming systems. Described in detail by Kuehne et al. (2017), the ADOPT model calculates the value of and time to peak adoption. Their calculations are based on the diffusion literature (S-shaped curve) used to provide quantitative predictions of the adoption of agricultural practices for a defined number of variables. Moglia et al. (2018) constructed a Bayesian Network model to describe the many factors that impact on the chances of a smallholder farmer adopting technology to change his/her farming practice. The model, when applied to four different technologies, generated insights into the factors that had the greatest influence on adoption rates (Alexander et al. 2018; Moglia et al. 2018).

A review of empirical and theoretical studies on adoption by Feder et al. (1985) found that the key explanatory factors affecting adoption in these studies were: farm size, risk and uncertainty, human capital, labour availability, credit constraints, tenure, supply constraints, and aggregate adoption over time. Pattanayak et al. (2003) evaluated statistical models of the adoption of technologies and found that adoption variables could be classified into five broad categories: household preferences, biophysical factors, resource endowments, economic incentives, and perceived risk and uncertainty. Pattanayak et al. (2003) found that the factors more likely to be correlated with adoption decisions included: soil quality, extension and training, tenure, savings and credit and assets. Jones (2005) included farmer perceptions as another important category and found that adoption decisions were influenced by several variables: education, extension, membership, health, cash cropping and soil quality. Meanwhile, variables that statistically correlated with decisions to dis-adopt included: education, experience, expected price and type of soil (Jones 2005).

Hence, there are many issues, variables, socio-economic factors that are influential and many stakeholders involved in the agricultural research value chain when trying to provide valuable opportunities for local farmers to enhance their agricultural production.

Measures of adoption

Adoption measurements have generally been based on binary/dichotomous (yes/no) options (Doss 2006; Feder et al. 1985; Knowler 2015; Ovwigho 2013; Smale et al. 1995). Jain et al. (2009) suggested that a dichotomous response may only reflect the status of awareness rather than actual adoption. Feder et al. (1985) in their review concluded that in statistical analysis, adoption decisions should not be considered as dichotomous, but rather viewed in terms of a more varied range of responses and in terms of the intensity of technology usage. In support, Brown et al. (2017) claim that the use of dichotomous responses leads to limited insights and misleading conclusions.

Agbamu (2006) suggests considering several methods to measure adoption: i) developing an adoption index through Sigma scoring of frequency counts; ii) calculating the percentages of adopters for several technologies; iii) assigning numerical values to the stages of adoption; iv) use of Likert scales and v) mean scores for disaggregated levels of adoption. For example, Iwueke (1990) classified the Likert scale for the stages of adoption as: unaware, aware, interest, evaluation, trial, adoption, reject and discontinuation. Alternatively, Ndagi et al. (2016) used descriptive statistics (frequencies and percentages) to categorize low, medium or high levels of adoption of rice farming techniques.

Furthermore, Tegengne (2017) classified farming communities into four major clusters based on their status of adoption. Using an adoption index - a measure of the extent of utilizing a particular technology per recommended unit - farmers were differentiated according to: (i) their technical orientation (information but not implemented), (ii) technology fledglings (new participants), (iii) technology adopters (sustained adoption) and (iv) technology dropouts (withdrawn interest).

Estimates of adoption normally assume a cumulative process of adoption is taking place, not accounting for the fact that, often times in reality, adoption may be short-lived and that, subsequently, dis-adoption occurs (CIMMYT Economics Program 1993). Brown et al. (2017) suggest that the adoption of most agricultural technologies tends to be partial and incremental, with ten stages to be considered. Brown et al. (2017) used the Process of Agricultural Utilisation Framework (PAUF) to describe adoption and non-adoption, illustrating several adoption pathways, reflecting that farmers will continually evaluate the usefulness of technology, and modify their production decisions accordingly.

Ornetsmüller et al. (2018) studied the adoption, expansion, intensification, diversification, and abandonment of intensive maize practices in northern Laos using gaming and simulation approaches. Jones (2005) explored the reasons for both adoption and dis-adoption and the factors that led to the abandonment of new technologies, given that dis-adoption has historically been overlooked and abandoned technologies can be considered ineffective or inappropriate technologies. A few studies have examined the rate and time at which technology might be abandoned (Feder and Umali 1993). Neill and Lee (2001) examined the adoption and abandonment of maize farming systems and found several exogenous factors had influenced abandonment of the technology including changes in land markets, the expansion of the cattle industry, modernization of the infrastructure and biophysical factors, such as the arrival of a particularly noxious weed and recent extremes of climate. Neill and Lee (2001) showed that road access was positively correlated with abandonment, as more economic opportunities tended to decrease production, and farmers that experienced problems with the noxious weeds were also more likely to dis-adopt.

Dis-adoption of rice intensification was explored by Moser and Barrett (2002). While rice intensification was promoted as a high yielding, low input alternative, adoption rates were considered low and consequent dis-adoption rates among adopters were almost double the adoption rate. The most commonly cited problems were related to time and labour pressures resulting from new transplanting and weeding regimes. Better-educated farmers, more experienced farmers and those with ready access to labour were more likely to continue with the new rice system. Farmers with off-farm labour opportunities tended to dis-adopt, given the opportunity costs associated with time spent in the new rice (Moser and Barrett 2002).

What is evident from our review of the literature is that there have been many approaches devoted to understanding inherent elements within the agricultural research value chain and to evaluate the impact on the adoption of new technologies by farmers. We have reviewed the literature on approaches to enumerating and understanding occurrences of adoption, innovation, diffusion and forecasting in various agricultural settings with a variety of technologies. Situations where adoption has occurred have been more often reported than those where it has not, with a plethora of accompanying explanations. Yet research into stages of adoption, partial adoption, dis-adoption and abandonment of technologies, and research into the intensity of technology use has been rarely attempted. In this study, we have constructed measures of adoption and define a cluster of factors (constructs) that more significantly influence the adoption of new technologies. We describe several states of adoption and how this is linked to the agricultural research value chain which influences farmers' evaluation of the usefulness of the introduced technology for their farming context.

Methods

Constructing the survey instrument

Based on our review of the literature on factors that have been shown to influence adoption of technologies, and literature from organizational change, supply chains and project management, we developed an exploratory survey instrument (finalised to 39 questions) to clarify farmers' perceptions of factors thought relevant to their agricultural decisions[2] and the success of the agricultural research value chain in creating valuable opportunities for farmers. The content of the instrument was based on a construct of key variables, including various factors of the agricultural research value chain, thought to influence the propensity of smallholder farmers to adopt proven technologies (Greenhalgh et al. 2017). The five key factors included the following variables:

- *Research Project Buy-in Factors*: variables related to whether a farmer might find research project outcomes influential in their production decisions
- *Research Project Implementation Factors:* variables associated with project management and change management
- *Farmer Motivation Factors*: variables aligned with motivation theory, readiness and commitment to change and identity theory
- *Farmer and Family Lifestyle Factors*: lifestyle and livelihood variables impacting farmers' behaviour and decisions
- *Supply Chain and Commercial Factors:* variables related to the efficacy of the supply chain and commercial variables driving behaviour

Survey questions were validated through discussions with Laotian researchers and other researchers and consultants with experience in South East Asia. The survey instrument included questions relating to demographics, technology understanding and attractiveness, and perceptions relating to benefits, support, risk and uncertainty, and cost of changing practices (Pattanayak et al. 2003). Questions regarding change management and implementation support were included (Kotter 1996), as were questions on farmers' perceptions of identity and motivation and readiness and commitment to change (Beckhard and Harris 1987; Burke and Stets 2009; Vroom 1965). Questions on farmers' lifestyle priorities and specific production time horizons were also included (Dethier and Effenberger 2012). Several other issues such as the effectiveness of local supply chains and farmers' profit orientation and access to reliable information were included. Table 1 indicates the variables and measures included in the survey, referring to the survey instrument presented as complementary material[3]

"<<Table 1 about here>>"

Case study region

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[2] See supplementary material https://docs.google.com/viewer?a=v&pid=sites&srcid=ZGVmYXVsdGRvbWFpbnxhY2lhcnNtYWxsaG9sZGVyYWRvcHRpb258Z3g6MTcwOWFjNjIwMmY1YmRkOQ

[3] Available at https://docs.google.com/viewer?a=v&pid=sites&srcid=ZGVmYXVsdGRvbWFpbnxhY2lhcnNtYWxsaG9sZGVyYWRvcHRpb258Z3g6MTcwOWFjNjIwMmY1YmRkOQ

The research was situated in Lao PDR, where up to three-quarters of the labour force work within the agricultural sector. Approximately 80 percent of the rural population are smallholder farmers, dependent on rice-based agriculture and livestock, producing on arable land of two to three hectares (Alexander et al. 2010; Alexander and Larson 2016; FAO 2017). Farming generally occurs on infertile, poorly structured soils with only marginal land productivity and low returns to labour (Philp et al. 2019). Farmers often face climate variability risks in the form of floods and droughts (Roth and Grunbuhel 2012), hence while farmers are generally considering opportunities to increase production and income through more intensive farming activities, many are opting for out-migration and alternative, non-farming, wage opportunities (Alexander et al. 2018; Manivong et al. 2014). Nevertheless, the intent of Lao government agricultural strategies and policies is to support more intensive productivity in key areas, thereby inducing a gradual transition from subsistence to commercial smallholder production (Ministry of Agriculture and Forestry 2010). In response, there has been an expansion of commercial plantation crops best suited to agro-processing for the export market and livestock production has also become increasingly commercialized in recent years (Ministry of Planning and Investment 2016; Stür and Gray 2014).

Technologies and the agricultural research value chain

To assist farmers in increasing agricultural productivity, the Australian Centre for International Agricultural Research (ACIAR) has introduced in Lao PDR the following technologies: new rice seed varieties, dry season rice and cropping regimes, vegetable and fruit varieties and planting methods, livestock/cropping interactions, direct drill planting methods, irrigation methods, alternative wet/dry planting methods, land reform- plot size and levelling, mechanical harvesting, and facilitated technical skills and knowledge transfer by working with District Agriculture and Forestry Officers (DAFO). ACIAR projects have worked with farmers groups, mills and private companies within the value chain to improve connectivity and agricultural trading opportunities (Alexander and Larson 2016). ACIAR projects have also investigated options for farmers to respond to projected changes in climate.

Numerous international organizations have also introduced technologies over the years into a number of the surveyed villages (Alexander and Larson 2016). For example, the Japan International Cooperation Agency (JICA) has introduced planting and post-harvest techniques and the production of organic vegetables using greenhouse technology. Various livestock and aquaculture projects have introduced new production techniques. Intensive rice production, contract farming opportunities, application of fertilizers, land management reform, irrigation projects, direct seeding machinery, soil preparation, water management systems, integrated pest management (IPM), maize production, women's health, vaccinations and nutrition, farmer field schools, and education projects have all been introduced over recent years by international research and development teams. In addition, the Lao government has implemented foreign project activities including distribution of new seed varieties, fertilizer application, seeding machines and facilitated interactions with rice milling companies. The Asian Development Bank has supported livestock projects involving disease prevention. Hence, according to the breadth of activities and the actors involved, the agricultural research value chain in Lao PDR is extensive and multi-institutional in nature.

Our project focussed on the adoption of new technologies by farmers. In our research survey farmers were asked to reflect on activities they had personally been involved in, so it was not possible to discern the influence of individual technologies, rather the purpose of the survey was to elicit holistic perceptions of their experiences.

Selection of villages

The purposive sample frame required that selected villages had also been recipients of recent agricultural projects, demonstrating new technologies, preferably an ACIAR project. Ten villages in predominantly lowland rice-growing agricultural systems in southern Lao PDR and with recent agricultural projects in Savannakhet Province and 10 villages in Champasak Province were purposively selected as survey sites. Villages were located at varying elevation, with varying soil profiles, differing access to water supplies and presence/absence of irrigation channels supporting dry season crops. Note that the "lowland" is made up of three topographies: 1) available water usually from river/dams, 2) irrigation production and 3) dryland non-irrigation production at a higher elevation. Accessibility to markets, access to credit or finance and areas where the production of two crops per year is possible, were additional selection criteria. The purposive sample was finalized with input by senior Lao researchers from the National University of Laos (NUoL) and the National Agriculture and Forestry Research Institute (NAFRI) and local government officials. ACIAR project details were verified by ACIAR researchers prior to finalization of target villages. The full list of the villages is available in the project report by Greenhalgh et al. (2017) and Alexander and Larson (2016).

Collecting the data

The survey instrument was reviewed by all researchers involved in the project and modified –on the basis of expert advice. It was then translated into Lao language and administered by project staff trained in the use of electronic voting techniques. The initial survey was tested among Lao researchers and in a pilot village prior to data collection activities. The content of the survey was reduced in order to reduce the participant completion time to approximately 1 hour.

In Savannakhet Province, the survey was administered by research teams in collaboration with local Lao government officers. In Champasak Province, the survey was administered independently by Lao personnel. In summary, Australian and Lao research teams, students and provisional and district agricultural staff collaborated in data gathering exercises. Local government officials invited farmers in the selected villages to attend meetings at their local meeting place. Farmers were then randomly selected to be involved in the survey activities while other research activities were undertaken concurrently. Farmers who attended community meetings organized by the research team were involved in the electronic voting exercise. In total 735 farmers participated in the survey exercise: 417 from 10 villages in Savannakhet Province and 318 from 10 villages in Champasak Province with 61% male and 39% female participants. In the local meeting place, villagers were invited to undertake the survey. Questions were presented in a simple and straightforward manner and pitched to reflect farmers' language and knowledge. Farmers seated in village meeting places (typically temples or school rooms) used small handheld devices to indicate their response to survey questions projected onto a screen from a laptop computer. To make it easier for farmers to respond, the survey included questions with dichotomous or a multiple item scale (1-7 Likert scale) response options – as explained to participants by the survey facilitators

(Churchill 1979, Nunnally 1978, Peter 1979). To minimise bias, survey facilitators were trained to be consistent in their descriptions and explanations of each survey element in response to any queries raised by participants.

Data analysis

We report on three types of data analysis in this article. Firstly, we offer an account of the observed relationships between the postulated "adoption measures" and provide several analytical insights. Secondly, we have undertaken a range of exploratory analysis approaches; including principal component analysis to evaluate which broad cluster of factors (constructs) more significantly influence the "adoption measures". Thirdly, we have applied a Poisson regression analysis to the identified constructs in order to explore the strength of influence each has on the various "adoption measures". For full results see the publically available report by Greenhalgh et al. (2017).

Adoption measures

A key data analysis strategy was to explore the factors that contribute to the propensity of farmers to adopt new technologies. In the survey, 4 variables accounted for participants' exposure to new technologies and their opinions on their usefulness[4]. Hence, the analysis was undertaken on the basis of the four dependent variables $Y_{i,j}$ where $i \in [1, 2, 3, 4]$ relates to one of the four adoption measures and j relates to the particular farmer. $Y_{i,j}$ is measured in the survey by means of the questions:

1. $\boldsymbol{Y_{1,j}}$ – *Project involvement,* adoption measure 1,: 1 if the farmer j has been part of a research project in the past. 0 otherwise. Participants who have taken part in research projects are referred to as "model farmers".
2. $\boldsymbol{Y_{2,j}}$ – *Number of technologies adopted*: adoption measure 2, is a count of the number of technologies that the farmer j reports to have adopted.
3. $\boldsymbol{Y_{3,j}}$ – *Technology still in use:* adoption measure 3,: 1 if the farmer j reports to still be using at least one of the adopted technologies. 0 otherwise.
4. $\boldsymbol{Y_{4,j}}$ – *Technology are useful:* adoption measure 4,: *1 if the farmer j reports having found at least one adopted technology to have been useful. 0 otherwise.*

Note: Taylor and Bhasme (2018) describe "model farmers" for the purpose of this research.

Summary statistics for adoption measures

In this sample, 45% of participants had taken part in a research project (model farmers). Amongst survey participants, 329 out of 735 (44%) had adopted at least one technology ($P(Y_{2,j} \geq 1) = 44\%$). 238 out of 329 (72%) who had adopted at least one technology were still using at least one technology ($P(Y_{3,j} \geq 1 \mid Y_{2,j} \geq 1) = 72\%$). 32% were still using a technology ($P(Y_{3,j} \geq 1)$) and 25% of all farmers report being using a technology that they found to be useful ($P(Y_{4,j} = 1) = 25\%$). Adoption measures are depicted in Figure 1.

"<<Figure 1 about here>>"

Focus on useful and abandoned technologies

[4] Q6 and Q7a-c in supplementary material https://docs.google.com/viewer?a=v&pid=sites&srcid=ZGVmYXVsdGRvbWFpbnxhY2lhcnNtYWxsaG9sZGVyYWRvcHRpb258Z3g6MTcwOWFjNjIwMmY1YmRkOQ

The analysis showed that 145 out of 329 technology adopters had abandoned at least one technology. Focusing on the sub-group of “model farmers” ($P(Y_{1,j} = 1)=45\%$), we found that 41% had abandoned at least one technology. In total 250 of those who had adopted a technology (farmer *j* being a model farmer indicated by $Y_{1,j}$ =1) had found that at least one technology had been useful, i.e., a success rate of 76%. This means that 24% of respondents who claimed to be still using technology do not believe that any of their adopted technologies were useful. When we calculate the total number of technologies that farmers had found to be useful and divide by the total number of technologies of adopted technologies (self-reported), 70% were been found to be useful.

Correlation between adoption measures

The influence of adoption measures was explored using the correlation matrix (Table 2).

“<<Table 2 about here>>”

Principal component analysis to identify factors and explanatory variables

A range of approaches, were used to statistically group the explanatory factors and variables of adoption (for further details, see Greenhalgh et al 2017). Initially, we used a theoretical starting point, where the proposed variables explaining the propensities to adopt were: Research Project Buy-in Factors; Research Project Implementation Factors; Farmer Motivation Factors; Farmer and Family Lifestyle Factors; and Supply Chain and Commercial Factors. Reliability testing and validity testing, including using Cronbach’s Alphas to evaluate internal consistency between factors within a group, factor analysis to explore variability among the set of observed factors, and scree plots to estimate the number of underlying variables in each measure indicated that the underlying propensity model of variables and indicators were not all statistically acceptable. The Cronbach’s Alphas ranged from 0.44 (considered unacceptable) to 0.73 (acceptable).

In recognition that the proposed explanatory variables were deemed unsuitable, we undertook further analysis. The Scree Plot based on all the measures combined in a single dataset can be seen in Figure 2. This plot indicates six underlying constructs. Exploration of the underlying Eigenvalues shows a decreasing set, with nine factors having Eigenvalues above nine. Hence, we considered between 6 and 9 constructs in our model.

“<<Figure 2 about here>>”

Adopting a 6-factor Factor analysis, we found that the resulting model explained 31% of the variance in the data and when we use a 9-factor Factor analysis, the resulting model explained 37% of the variance in the data. To keep as much information as is appropriate, we went ahead with a 9-factor model. The pattern matrix of the 9-factor model is shown in Table 3; using 0.35 loading as a threshold for considering a measure’s inclusion into a construct. For details see Greenhalgh et al (2017).

“<<Table 3 about here>>”

The measures of the 9-construct model are shown in Table 4. The results of this analysis was that it allowed us to define the key explanatory variables that influence the propensity to adopt technologies, depicted in Table 4, and calculated using the indicators (measures) in the survey instrument.

“<<Table 4 about here>>”

Poisson regression analysis

We applied a generalised linear model, via Poisson (multiple) regression analysis to the identified explanatory factors to explore how they influence propensity measures (Winkelmann 2008). R statistical software (R Core Team 2013) was used to explore a Poisson regression utilising the Generalised Linear Model functionality. A type of linking function has to be chosen for each of the regression analyses. Two types of linking functions were used, as follows:

$$\mu + \sum_{i=1}^{9} X_{i,j} \cdot \beta_j = ln\left(\frac{\mu}{1-\mu}\right) + \varepsilon_j \tag{1}$$

$$\mu + \sum_{i=1}^{9} X_{i,j} \cdot \beta_j = ln(\mu) + \varepsilon_j \tag{2}$$

Here, j represents a farmer, and i represents factor i (as per Table 4). μ is the mean value, and ϵ_j represents the error term for farmer j (i.e. the deviation between model expectation value and observed value). β_j represents the model parameter associated with each factor and μ represents the model intercept. Based on what was found to provide the best fit, the linking function in equation 1 was used for the type 1 adoption measure, and linking function in equation 2 was used for adoption measures 2, 3 and 4. The results of the Poisson regression analysis are shown in Table 5. In general, and in Table 5, statistical significance levels are indicated by stars. Significance levels are based on the estimated p-value, i.e. the probability of getting this result if there was no influence. "*" means $p < 0.05$, "**" means $p<0.01$ and "***" means $p<0.001$. A negative influence is denoted by a negative value, and a positive influence is denoted by a positive value.

"<<Table 5 about here>>"

Discussion

To explore the factors that contribute to the propensity of farmers to adopt new technologies we established 4 measures of adoption based on participants' exposure to new technologies and perceptions of the usefulness of the technology. Rather than being technology-specific, the focus was on the apparently sustained usefulness of technologies, thereby providing a snapshot of farmers' choices to adopt/dis-adopt technologies and furthermore reflects on the usefulness. Statistical measures of the "status of adoption" (Figure 1) illustrate the fluidity that occurs when farmers are exposed to project offerings and when they decide whether to adopt and whether to continue using technologies. The four measures were: Project involvement ($Y_{1,j}$); Number of technologies ($Y_{2,j}$); Still using technologies ($Y_{3,j}$) and Technology is useful ($Y_{4,j}$). Based on our literature review, these adoption measures have not been used previously, and provide a useful illustration that a dichotomous approach to adoption is unrealistic and the states of adoption should be taken into account, as recommended by (Feder et al. 1985). The initial frequency analysis indicated a considerable technology dropout rate over the technology exposure timeframe. Continued dis-adoption was reported and not all technologies were perceived to provide benefits, even though some farmers continued to use them.

Factors influencing adoption measures

The first important insight is that our proposed explanatory factors were not necessarily the best explanation but rather, according to our data, a factor analysis (Table 4) pointed to nine important factors that influence adoption outcomes. These are described further as:

1. *Being proactive*: Farmers are motivated by technical support, motivated by compensation, possessing a belief that adoption creates benefits, and is influenced by local farmer advice, and participating in small trials
2. *In need of support:* Farmers need technical support, not necessarily the first adopter, and also needs clear explanations
3. *Focus on production outcomes:* Farmers are motivated by reduced input costs, motivated by crop productivity, and motivated by ease/convenience of using the technology
4. *Ease of selling produce:* Farmers are focused on improving livestock and having access to multiple rice buyers
5. *Trying to generate off-farm income:* Farmers' priority is to gain off-farm income opportunities
6. *Competitive milling market:* Farmers want easy access to multiple mills and access to information on local market prices for rice
7. *Labour constraints:* Farmers are concerned about activities that require labour inputs
8. *Risk avoidance:* Farmers are risk-averse and tend to prioritise the importance of taking small risks
9. *Access to storage and transport*: Farmers want access to farm and local storage, and access to transport providers

The importance of these findings is that to understand adoption processes in the field amongst smallholder farmers, it is useful to assess these explanatory factors, to inform research and policy considerations, such as: which farmers to engage with, which locations to focus on, how to remove barriers to adoption, and how to incentivise adoption. These issues influence the effectiveness of the supportive agricultural research value chain, in which farmers are making production decisions and indicate that researchers need to take into account a variety of contextual, perceptual and site-specific elements that will influence the relative success and sustainability of adoption for an introduced technology.

Different factors influence different types of adoption

We applied a generalised linear model, via Poisson (multiple) regression analysis on the explanatory factors (Table 5) to explore how they influence the adoption measures outlined in Table 2: i) project involvement, ii) adoption, iii) still using technology and iv) still using a technology that has been useful. Tentative conclusions based on our Poisson regression analysis are that in relation to the factor:

- *"Being proactive":* Focusing attention on farmers who are proactive and responsive to incentives is a sensible strategy when imparting development and research interventions because these farmers are also more likely to persist with the technology and report benefits at a higher rate than other farmers.
- *"In need of support":* The primary barrier for adoption of technology is the capacity of farmers, i.e. farmers who require technical support and who struggle to understand the benefits of technologies are less likely to adopt, persist with and self-report benefits from adoption. This is in line with other

research that shows education and literacy as factors influencing rates of technology adoption (Jones 2005, Moser and Barrett 2002).

- *"Ease of selling produce":* We observe a somewhat surprising effect that farmers who can easily sell their produce are less likely to adopt new technology. This finding requires further exploration but tentatively indicates that farmers tend to only try something new if they experience difficulties selling their usual produce. Hence the research community should appraise access to markets and traders and the ability to trade produce, prior to investing energy into influencing farmers to enhance production.
- *"Competitive milling market":* Focusing on generating greater competition between mills not only generates higher rates of technology adoption but also generates higher rates of persistence of technology and self-reported benefits from technology adoption. This is, therefore, a key lever for policymakers when promoting greater technology adoption. From a research perspective, this shows that focusing on areas with greater competition between mills is likely to generate more positive impacts from research activities. Note that in this case we focussed on rice production, but the finding may potentially be generalizable to greater competition between actors keenly positioned in the value chain.
- *"Access to storage and transport":* Whilst access to storage and transport facilities does not support higher rates of adoption of technology per se, these factors are important for allowing farmers to persist with using the technology and are also critically important for allowing farmers to realise benefits from their technology adoption. This is another important lever for developing country governments, i.e. infrastructure investment in these facilities will allow farmers to persist with and realise benefits from technology adoption.

Limitations of the research approach

Some important limitations of our research are listed here:

- The results from the survey should perhaps be interpreted with some caution because of the difficulty for farmers to accurately respond to the survey questions. To mitigate the possible effects of misunderstanding, the survey was subject to extensive testing and was administered by local collaborators as facilitators who were trained to provide appropriate and consistent priming when necessary.
- In hindsight, we realise that the survey that was undertaken, for good reasons, in a way that was not technology-specific. Accordingly, our analysis identifies several factors that can influence technology adoption. However, we believe that a more targeted and innovation-specific survey would pinpoint more precisely the factors that are most germane for any given technology. Further research is required to develop a refined survey to explore technology- and product-specific issues in light of the encompassing agricultural research value chain.

Implications for agricultural research

We agree with postulations by Röling (2009) that the introduction of new technologies through agricultural research activities is, sometimes incorrectly, assumed to result in technology adoption to generate benefits and value to farmers and other stakeholders. Whilst the agricultural value chain is to some extent explored in the literature - generally describing the movement of produce from the farm to the customer - we suggest that research activities designed to create benefits for farmers through the use of new technologies are operating in a more complex system which is generally in rapid transition. The term we introduce to capture this particular dynamic is the *agricultural research value chain*.

In addition, the simplistic notion that adoption is a dichotomous decision – an assumption often made in economic research studies - is not a realistic approximation of what occurs in terms of dis-adoption and partial adoption. In fact, we have illustrated a process occurring whereby farmers are presented with project activities and the consequent adoption pathways are impacted by many elements within the agricultural research value chain. Farmers continually evaluate the usefulness of technology, and modify their production decisions accordingly, based on the ever-changing context and complexity of the value chain that markets their produce. Consequently, if adoption with associated benefit is to occur, agricultural research projects need to take a broader view, outside their speciality and take stock of the more complicated processes within the accompanying value chain. We have used 4 measures of adoption that, we contend, have much greater explanatory power than a simplistic dichotomous approach to the concept of adoption.

A key implication of our research is that scientists, extension workers, farmers and policymakers could all benefit by shifting the emphasis from the introduced technology to the potential users and their behavioural proclivities. In other words, a more holistic approach to the introduction of new technologies would be highly beneficial (Alexander et al. 2018).

A second key implication is that where a government-approved research project aims to provide farmers with useful technologies, getting farmers to adopt technologies is seemingly more efficient than getting them involved in projects, particularly as there is not a strong correlation between technology *adoption* ($Y_{2,j}$) and project involvement ($Y_{1,j}$) (Table 2). This may indicate that model farmers play a significant role in trialling technologies under the watchful eye of other farmers who are not as much influenced by the value of the claim, but more so by initially witnessing success by other farmers (see Taylor and Bhasme (2018) for more details). The correlation matrix (Table2) also suggests that there is an influence of the number of technologies ($Y_{2,j}$) and whether the technologies are useful and whether the farmer is still using the technology ($Y_{3,j}$) and perceived usefulness ($Y_{4,j}$). Hence, if the project can encourage farmers to adopt a few technologies ($Y_{2,j}$), there may be a greater rate of adoption than through the adoption of a lone technology.

There appears to be a complex ecology of determinants at work playing out in different villages and with different technologies. Whilst the survey has not explicitly collected information on different types of technologies, this level of complexity indicates that for any given technology the determinants may not be of equal strength; that is, for different technologies and in different situations, different determinants may be more important than others.

Conclusions

We have reviewed the literature on adoption and innovation in various agricultural settings with reference to the introduction of a variety of technologies. Research into the various stages of adoption, partial adoption, dis-adoption and abandonment of technologies has been rarely attempted. In the literature, where adoption has been assessed, more attention has been applied to whether or not adoption has occurred. In this study, we have used 4 measures of adoption, as follows: 1) involvement in a research project, 2) adopting new technology, 3) persisting with technology, and finally, 4) realising benefits arising from the adoption of the newly adopted. We have also conducted an exploratory study to determine the key factors that influence adoption by defining 9 conceptual factors, based on our survey data, that more significantly influence the adoption of new technologies. We then assessed how the measures (states) of adoption related to the key factors that influence adoption (Table 4). The 9 key factors were: 1) being proactive, 2) in need of support, 3) focus on production outcomes, 4) ease of selling produce, 5) trying to generate off-farm income, 6) competitive milling market, 7) labour constraints, 8) risk avoidance and 9) access to storage and transport.

The key factors represented attributes of the farmer (factors 1, 2, 3, 7, and 8), the factors considered when making production decisions and elements of the agricultural value chain (4, 5, 6 and 9) that present as opportunities or constraints. Hence, our introduction of the term *agricultural research value chain* enables an improved understanding of farmers' personal attributes and perceptions in the context of the operational value chain. Upon reflection, research activities should be geared towards farmers who are proactive and responsive to incentives as these farmers are also more likely to persist with the technology and to report benefits. The primary barrier for adoption of technologies is the capacity of farmers, i.e. farmers who require technical support and who struggle to understand the benefits of technologies are less likely to adopt, persist with and self-report benefits from adoption. Generating greater competition between actors in the value chain interested in processing agricultural produce is an important policy strategy. Access to storage and transport facilities are important in allowing farmers to persist with using the technology and are also critically important in allowing farmers to realise benefits from technology adoption. Government investment into infrastructure facilities will also allow farmers to persist with, and realise benefits from, technology adoption. Prior to investing energy into influencing farmers to enhance production, the research community should appraise access to markets and traders and farmers' ability to trade produce.

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Table 1: Variables and measures included in the exploratory survey instrument

Variable	Measures	Variable	Measures
Benefit priorities	Increased income (Q8a1) Reduced input costs (Q8a2) Crop productivity (Q8a3) Reduced labour (Q8a4) Ease/convenience (Q8a5) Small risk (Q8a6) The benefit is large (Q8a8) Compensation (Q8a9) Size of benefit (Q8b)	**Desire for support**	Need technical support (Q11-1) Need not to be first adopter (Q11-5) Need clear explanations (Q11-7)
Risk/uncertainty attitude	Need trials to be convinced (Q12-2) Need get-out clause (Q12-3)	**Perceived barriers**	Concern about inputs (Q13-2) Concern about labour (Q13-3)
Change management elements	Require problem focus (Q11-1) Require support (Q11-2) Require understanding of outcomes (Q11-4) Require quick win (Q11-6)	**Level of implementation support**	Require help from others (Q15-2)
Readiness for change	Eagerness for innovation (Q17)	**Commitment to change**	Self-reported tendency to persist (Q18)
Identity standards	Focus on earning money (Q19) Household role identity (Q20a) Willingness to change (Q20b)	**Farmer and family priorities**	Farm income (Q21-1) Off-farm income (Q21-2) Labour productivity (Q21-3) Improving livestock (Q21-4)
Time horizon	Length of planning horizon (Q22)	**Supply chain access**	Access to inputs (Q24-1) Access to fair prices for inputs (Q24-2) Access to farm/local storage (Q24-3) Access to transport providers (Q24-4) Access to multiple mills (Q24-5) Multiple rice buyers (Q24-6) Fair prices for rice (Q24-8)
Information access	Access to information on local market prices for rice (Q26-1)		

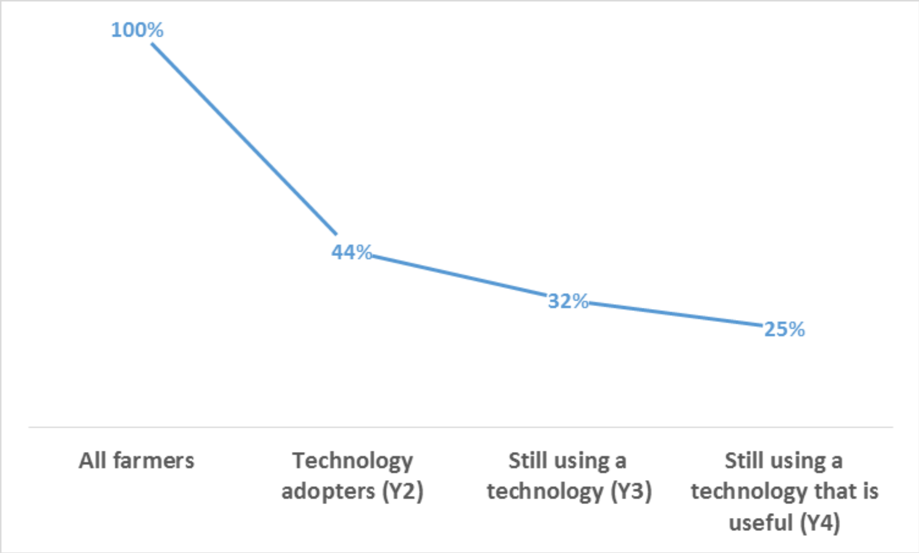

Figure 1: Adoption measures. Y-axis: Percentages of respondents fulfilling the criteria denoted on the x-axis.

Table 2: Correlation matrix of adoption measures

	$Y_{1,j}$ Project involvement	$Y_{2,j}$ Number of technologies	$Y_{3,j}$ Still using technologies	$Y_{4,j}$ Technologies are useful
$Y_{1,j}$ Project involvement	1.00	0.36	0.29	0.31
$Y_{2,j}$ Number of technologies	**0.36**	1.00	0.47	**0.53**
$Y_{3,j}$ Still using technologies	0.29	0.47	1.00	**0.51**
$Y_{4,j}$ Technologies are useful	0.31	0.53	0.51	1.00

Note: This table shows the Pearson correlation coefficient for the associated row and column variables. Pearson's correlation coefficient is a measure of the linear correlation between two variables, with 1 being perfectly linearly correlated and -1 being perfectly negatively correlated. It measures to what extent one variable can be described using a linear function of the other variable. A higher correlation usually indicates a stronger influence (emboldened in the table).

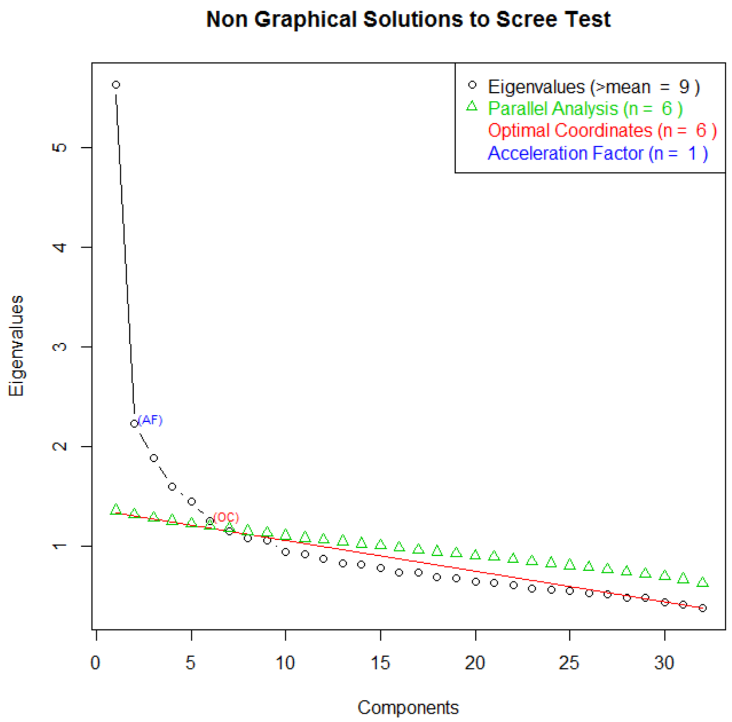

Figure 2: Scree Plot for all data combined

Table 3: Pattern matrix for 9-factor model showing loadings in measures onto constructs/factors

	MR1	MR7	MR2	MR3	MR4	MR5	MR6	MR8	MR9
RiskReductionTrial	**0.54**	-0.01	0.04	0.05	0.16	0.04	-0.04	-0.02	-0.08
ParticipationReasonPertinent	**0.68**	-0.06	0.08	0.09	-0.07	0.1	-0.02	-0.03	-0.04
ParticipationReasonSupport	**0.58**	0.08	0.05	-0.06	0	-0.12	0.04	-0.03	0.12
ParticipationReasonUnderstanding	**0.49**	0.29	-0.08	-0.04	0.07	-0.1	0	-0.05	0.1
ParticipationReasonFastBenefits	**0.41**	0.16	-0.07	0	0.06	0.04	0.03	0.18	-0.07
ParticipationReasonExperiencedLocalAdvice	**0.55**	-0.08	-0.07	0	0.03	0.02	0.11	0.18	0.03
SupportTechAdvice	0.04	**0.63**	0.07	0.04	0.02	-0.05	0.07	0.01	0.06
SupportPeopleBetterOff	0	**0.64**	0.01	0.01	-0.01	0.07	-0.05	0.03	-0.05
SupportExplainedClearly	0.11	**0.5**	0.05	-0.04	0.02	0.06	-0.06	0	0.13
BenefitsInputCosts	-0.02	0.15	**0.48**	-0.03	0.17	-0.17	-0.08	0.02	-0.02
BenefitsCropProduction	0.08	-0.02	**0.6**	-0.01	0.02	0	-0.05	0.03	-0.03
BenefitsEasierWork	-0.02	0.08	**0.43**	0.12	0.03	-0.07	0.01	0.27	0.09
PriorityLivestock	0.08	0.03	-0.01	**0.69**	0.11	0.13	0.02	-0.01	-0.06
SupplyChainMultipleBuyers	-0.02	0.13	-0.02	**0.35**	-0.06	0	-0.22	0	0.33
SupplyChainAccessToFairPric	0.04	0.07	-0.04	**-0.58**	0.16	0.2	0.04	-0.01	-0.06

e									
PriorityOffFarmIncome	0.01	-0.03	0.02	0	**0.78**	0	-0.04	0.05	0.03
SupplyChainMillCompetition	0.08	-0.09	0.06	-0.02	0.09	**0.55**	0.08	-0.02	0.24
AccessToInformation	-0.01	0.15	-0.19	0.06	-0.05	**0.53**	-0.07	0.02	-0.06
BarriersLabor	0	-0.01	-0.05	-0.03	-0.07	0	**0.62**	0.01	0.01
BenefitsLowRisk	0.05	0.05	0.17	0	0.16	0.01	0.02	**0.49**	-0.02
SupplyChainRiceStorage	0	-0.04	0.01	0.01	0.05	0.07	0.16	0	**0.45**
SupplyChainTransportAccess	0.02	0.12	-0.08	-0.09	0.13	0.23	-0.1	-0.01	**0.41**
BenefitsLargeBenefit	*0.02*	*0.33*	*0.15*	*0.04*	*0.08*	*-0.01*	*0.13*	*0.22*	*-0.02*
BenefitsCompensation	*0.04*	*0.33*	*-0.04*	*-0.04*	*0*	*-0.08*	*0.23*	*0.23*	*-0.05*
BenefitsFarmIncome	*-0.04*	*0.3*	*0.33*	*0.02*	*-0.13*	*0.14*	*0.14*	*0.03*	*-0.02*
BenefitsLabor	*0.08*	*0.16*	*0.29*	*-0.03*	*-0.01*	*0.23*	*0.03*	*0.29*	*0*
RiskReductionGetOutClause	*0.29*	*0.09*	*0.01*	*0.03*	*0.07*	*0.07*	*0.02*	*-0.14*	*0*
BarriersInputs	*0.15*	*0.04*	*-0.14*	*0.13*	*0.06*	*-0.09*	*0.27*	*0.12*	*0.06*
PriorityFarmIncome	*0.19*	*0.13*	*0.21*	*0.05*	*0.23*	*0.01*	*0.15*	*-0.2*	*0.02*
PriorityLabourProductivity	*0.05*	*0.15*	*0.06*	*0.16*	*0.33*	*0.06*	*0.27*	*-0.22*	*-0.01*
SupplyChainInputs	*-0.09*	*0.08*	*-0.17*	*0.28*	*0.14*	*-0.03*	*0.06*	*0.19*	*0.06*
SupplyChainKnowRightPrice	*-0.07*	*0.01*	*0*	*-0.24*	*0.16*	*0.17*	*0.08*	*0.07*	*-0.12*

Table 4: Explanatory factors and variables based on the pattern matrix

Factor	Variables
1. Being proactive	Motivated by technical support (Q11-1) Motivated by compensation (Q11-2) The belief that adoption creates benefits (Q11-4) Influenced by local farmer advice (Q15-2) Influenced by small trials (Q12-2)
2. In need of support	Need technical support (Q11-1) Need not to be first adopter (Q11-5) Need clear explanations (Q11-7)
3. Focus on production outcomes	Motivated by reduced input costs (Q8a2) Motivated by crop productivity (Q8a3) Motivated by ease/convenience (Q8a5)
4. Ease of selling produce	Focus on improving livestock (Q21-5) Access to multiple rice buyers (Q24-6) Access to a perceived fair price for rice (Q24-8)
5. Trying to generate off-farm income	Prioritising off-farm income (Q21-2)
6. Competitive milling market	Access to multiple mills (Q24-5) Access to information on local market prices for rice (Q26-1)

7. Labour constraints	Concern about labour inputs (Q13-3)
8. Risk avoidance	Prioritising small risk (Q8a6)
9. Access to storage and transport	Access to farm/local storage (Q24-3) Access to transport providers (Q24-4)

Note: Since writing the project report, we have changed the name of the factors to use a more descriptive terminology, focusing on what each of the indicators may represent. This means there is some level of discrepancy between the published report variable names and the presented variable names.

Table 5: Results of Poisson regression analysis

Factors influencing farmers' propensity to adopt technologies	**Adoption measures**			
	Type A – project involvement	**Type B – number of technologies adopted**	**Type C – still using the technology**	**Type D – reporting adoption benefits**
Intercept	-1.62**	-0.75*	-2.16***	-1.75***
1 Being proactive	0.22	**0.32****	**0.35****	**0.53*****
2 In need of support	**-0.70***	**-0.60*****	**-0.42****	**-0.51*****
3 Focus on production outcomes	0.37	-0.12	**0.55****	**0.50****
4 Ease of selling produce	-0.28	**-0.74*****	**-0.31*****	**-0.54*****
5 Prioritising off-farm income	**0.90****	**0.57****	**0.77*****	0.16
6 Competitive milling market	**1.47*****	**0.76*****	**0.46*****	**0.46*****
7 Labour constraints	0.60.	0.19	**0.45***	-0.33.
8 Risk avoidance	-0.05	**0.84***	-0.24	-0.16
9 Access to storage and transport	-0.11	-0.045	**0.44****	**0.50****