# A Bayesian Network model to explore practice change by smallholder rice farmers in Lao PDR

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## Highlights

- A Bayesian Network was built to explore the chances of practice change amongst farmers.
- The focus of the study is smallholder farmers in southern Lao PDR.
- The model emphasizes systemic barriers and enablers relating to practices and context.
- Coordinated multi-stakeholder action can improve the likelihood of practice change.
- The model supports examination of data gaps, perspectives and knowledge management.

**Keywords: innovation diffusion, Bayesian Networks, small-holder farmers, rice agriculture, Laos, Lao PDR**

## Abstract

A Bayesian Network model has been developed that synthesizes findings from concurrent multi-disciplinary research activities. The model describes the many factors that impact on the chances of a smallholder farmer adopting a proposed change to farming practices. The model, when applied to four different proposed technologies, generated insights into the factors that have the greatest influence on adoption rates. Behavioural motivations for change are highly dependent on farmers' individual viewpoints and are also technology dependent. The model provides a boundary object that provides an opportunity to engage experts and other stakeholders in discussions about their assessment of the technology adoption process, and the opportunities, barriers and constraints faced by smallholder farmers when considering whether to adopt a technology.

## 1. Introduction

The Lao Peoples' Democratic Republic (Lao PDR), situated in South-East Asia, has a population of approximately 7 million, with over two-thirds living in rural areas and engaging in farming activities (Central Intelligence Agency (CIA) 2017; Asia and Pacific Commission on Agricultural Statistics (APCAS) 2012). Currently, rural populations remain relatively poor, living on less than two dollars purchasing power parity (PPP) a day, with few basic services available (Belloni 2014; Australian Government 2017). Rural livelihoods have traditionally been largely underpinned by low-yield subsistence-oriented or semi-commercial rice production combined with small-scale livestock production (Alexander , Case et al. 2017; Alexander, Parry et al. 2018).

Lao PDR is on a current trend of intensified production industrialization, market integration and trends in urbanization and population mobility (de Koninck 2004; Cook 2006; Humphrey 2006). Lao PDR is also highly dependent on agriculture, with approximately 70% of labour contributing to the agriculture sector (Ministry of Planning and Investment 2015). The government of Lao PDR has ambitious targets for increasing agricultural production and hopes to increase international exports (MAF 2015). The government has selected large plains in Southern provinces of Lao PDR as location for intensifying rice production. It is thought that agricultural productivity could be boosted by changed farming practices and adoption of innovative farming practices. Adoption of changed farming practices, however, has often been more difficult to achieve and often at a much slower rate than hoped.

The Lao Ministry of Agriculture and Forestry (MAF 2015) has implemented agricultural policies to promote a more market-oriented agricultural sector (MAF 2015). To build economic security and resilience, smallholder farmers need opportunities to improve productivity and generate income, supported by reliable access to markets and social and financial services. Yet poorly functioning value chains and poor market access, inadequate product quality, lack of infrastructure and extension, lack of supportive policies and the gendered nature of farming activities all tend to impede farmers' efforts to improve farming systems and livelihoods (Alexander, Miller et al. 2010; Manivong 2014).

The Australian Centre for International Agricultural Research (ACIAR) engages in rice-based systems research activities to increase farm productivity by introducing technologies designed to diversify production, reduce labour and increase efficiency (ACIAR 2014). Berkhout et al (2015) suggest that adoption of technical innovations is more likely if the use of inputs increases overall productivity for smallholder farmers without requiring excessive labour demands. The uptake (adoption) process of introduced technologies is subject to a very complex and highly contextual process. It is dependent on many factors such as personal, social, political, cultural and environmental and economic factors, as well as the characteristics of the introduced technology (Jobard 2010; Feder, Birner et al. 2011; Manivong, Cramb et al. 2014; Srisopaporn, Jourdain et al. 2015). In a review of adoption by Australian researchers, Parnell et al (2006) found that 'adoption' is mediated by a learning process where the farmer collects, integrates and evaluates new information in situations of uncertainty. At least for relatively simple innovations, a farmer's increased probability of making a good decision that will advance his/her goals occurs through improved knowledge, practice and experiences.

Hence the adoption process is continuous, uncertain and repeatedly reviewed as new information is encountered and circumstances change (Rogers 2003). In addition, farmers learn and enhance their skills when applying the innovation in situ, with a range of responses to seasonal implementation, e.g., choices in timing, sequencing, intensity, scale. Stages of adoption by farmers have been described by Parnell et al (2006) to involve: (i) awareness of the problem or opportunity, (ii) non-trial evaluation, (iii) trial evaluation, (iv) adoption, (v) review and modification and (vi) non-adoption or dis-adoption. Adoption and dis-adoption may occur and arise with circumstance (Kiptot, Hebinck et al. 2007).

This study focuses on the likelihood of technology adoption by smallholder farmers in Lao PDR, at different scales, with the aim to understand the complex web of factors that can hamper or stimulate the adoption of introduced technologies. In most cases, this process is difficult to observe, with tacit factors such as personality or cultural preferences playing an important role, or factors that relate to the ease of use/attributes of the technology that are perceived to be important to the farmer (Moglia, Cook et al. 2017). These issues are even more difficult to discern in a bilingual situation such as when researchers have to work with translators. Nonetheless, several theoretical perspectives are relevant to the enquiry of adoption of new technologies by smallholder farmers, including the theory of planned behaviour (Fishbein and Ajzen 1975; Ajzen 1991), the Consumat model of adoption behaviour (Janssen and Jager 1999; Jager, Janssen et al. 2000; Janssen and Jager 2001; Janssen and Viek 2001; Jager, Janssen et al. 2002; Jager and Janssen 2003; Jager, Janssen et al. 2014), and the theory of technological transitions (Geels 2002; Geels 2005; Geels and Schot 2007; Geels and Schot 2010).

## 2. Study context

This research activity, the Bayesian Network (BN) development, is only one component of a larger study commissioned by the ACIAR[1]. The aim of the study was to better understand conditions influencing farmers' decisions to adopt new technologies (Alexander, Larson et al. 2017). Other research activities involved a review of the literature (Alexander and Larson 2016), focus group discussions, interviews, farmer surveys (Greenhalgh, Moglia et al. 2017), Q methodology (Alexander, Larson et al. 2016; Alexander, Parry et al. 2018), and agent-based modelling activities (report yet to be published but may be released on the project website[2]). A mixed methods approach synthesizing qualitative and quantitative data was used. Geographically, villages in predominantly lowland rice-growing agricultural systems in southern Lao PDR and with recent agricultural projects, 10 in Savannakhet Province and 10 in Champasak Province were purposively selected as research sites in southern Lao PDR. Rice production and livestock raising were the main sources of food and income, often supplemented by the production of crops, fruits, and vegetables as additional sources of income. Increasingly, farmer households sought wages and remittances through off-farm income opportunities such as seasonal migration. In the associated research activities, it was found that farmers were interested in increasing rice productivity through soil improvement (fertilizers) and/or new seed varieties. In terms of seed types, interviews revealed that farmers sought varieties that would yield palatable rice of high quality, were disease resistant, with good qualities of aroma, shape, and acceptable milling characteristics (Alexander, Parry et al. 2018). Farmers were also interested in technologies/practices that reduce labour requirements and improvement of livestock productivity. Direct seeding methods to save labour and/or time when transplanting rice generated a lot of interest (Clarke 2015). Vaccination of livestock to prevent disease was another technology that was considered important. As the Lao government is keen to increase the export of rice to

[1] ASEM/2014/052 'Smallholder farmer decision-making and technology adoption in southern Lao PDR: opportunities and constraints'.
[2] Project publication repository: https://sites.google.com/view/acrtechnologyadoption/project-reports

international markets, another innovation that was considered was growing ‘white rice’ for export primarily to China. Note that Lao people prefer to consume traditional varieties rather than ‘white rice’. Consequently, the technologies/practices explored through the BN model included; direct seeding methods, new seed varieties and fertilizers to improve rice production and opportunities for greater livestock production through vaccination (Table 1).

*Table 1: Changes in farming practices in Southern Lao PDR explored using the BN model*

| **Farming practice** | **Description** |
|---|---|
| Direct seeding methods (DSM) | Use of Direct Seeding Machines can significantly reduce the time required to plant ricefields.<br>Difficulties using the equipment can occur as in some fields (small fields, uneven terrain, waterlogged soils etc.), greater weed intrusion can occur using this method and poor soils are not always mitigated through fertilizer application. Especially when inadequately applied. |
| Improved fertilizers | Improved fertilizers to help farmers improve soils. |
| Growing white rice for international markets | Use of white rice varieties sold at a significantly higher price on international markets, although not widely consumed in Laos. |
| Vaccination of cattle | Vaccination of livestock to protect against certain diseases (foot-and-mouth disease, haemorrhagic septicaemia. |

## 3. Comments on the Methodology

This paper describes the development of a Bayesian Network to explore the likelihood of practice change amongst smallholder farmers in Laos. Whilst developed for this specific context, the model has generalizable properties that also have implications for modelling smallholder farmer adoption behaviour in other parts of the world.

A Bayesian Network is a probabilistic directed acyclic graphical model (Pearl 1988; Pearl 2000; Neapolitan 2003). By definition, this terminology indicates that the model represents a set of factors that influence an outcome in a probabilistic manner, where a network (a directed graph) describes the interconnected and probabilistic cause and effect relationships between a number of factors and the proposed outcome. For example, there could be probabilistic relationships between agricultural productivity and farming practices. These probabilistic cause and effect relationships are described using conditional probabilities where upstream probabilities are aggregated on the basis of Bayes' Theorem. Bayes' theorem describes the probability of an event, based on prior knowledge of conditions that might be related to the event, as described in Equation 1.

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)} \qquad \text{(Equation 1)}$$

Here, A and B are events. P(A) and P(B) are the probabilities of observing A and B independently of each other. P(A|B) is the likelihood of event A, if B is true. P(B|A) is the likelihood of event B, if A is true. Systems of these types of equations can be set up and thereby defining a Bayesian Network.

A noted limitation of the static Bayesian Network is that there can't be any cyclic cause and effect relationships, i.e., no feedback loops between variables can exist. This limitation can be addressed by using a Dynamic Bayesian Network which describes how a set of factors change over time (Ong, Glasner et al. 2012). It is deemed that at this stage, a static Bayesian Network without representation of causal feedback loops, is a sufficiently adequate representation of the small-holder farmer technology adoption processes.

Whilst not inherent in the mathematical structure, Bayesian Networks are often used to embed judgments and beliefs of experts in a structured manner (Stewart-Koster, Dieu Anh et al. 2017) within a system of equations that represent probabilistic statements of logic, i.e. if X then the probability of Y is p. In fact, the mathematical framework, sometimes enhanced with subjective logic (Pope and Jøsang 2005; Moglia, Sharma et al. 2012), can be used to integrate multiple, even inconsistent, judgments and expert opinions into one coherent framework This allows for the capture of collective knowledge that makes assessments more robust (Moglia, Perez et al. 2012). In fact, when embedded into a participatory process, Bayesian Networks can be used to support and promote the sharing of divergent values, interests and beliefs and to illuminate what is and what isn't known, thus bringing about ontological conversations on complex issues (Henriksen, Rasmussen et al. 2007). Therefore, it is not strange that Bayesian Networks sometimes referred to as Bayesian Belief Networks are commonly applied in contexts where there is limited scientific data and where expert judgment is plentiful and accessible.

Useful examples of the applicability of Bayesian Networks include: environmental management (Low Choy, Stewart-Koster et al. 2005; Henriksen, Rasmussen et al. 2007; Ticehurst, Newham et al. 2007; Stewart-Koster, Bunn et al. 2010), reliability engineering (Trucco, Cagno et al. 2008), software engineering (Fenton, Marsh et al. 2004) and project management (Khodakarami and Abdi 2014). In fact, Bayesian Networks have been used for knowledge integration tools and systems analysis in an agricultural context within a number of studies (Henderson and Burn 2004; Bashari, Smith et al. 2008; Florin, van Ittersum et al. 2013; Stewart-Koster, Dieu Anh et al. 2017).

In this paper, we apply Bayesian Networks using the philosophy that has been growing in traction which sees BNs as knowledge management tools within participatory processes and adaptive governance (Bromley, Jackson et al. 2005; Castelletti and Soncini-Sessa 2007; Farmani and Savic 2008; Henriksen and Barlebo 2008; Haapasaari, Mäntyniemi et al. 2013; Düspohl and Döll 2016). These tools are often relatively basic in terms of computational complexity due to the common lack of objective data, but are instead seen as integrator tools for different types of information.

## 4. Knowledge Contribution

The paper's contribution to knowledge is not the methodology per se, but the application of the methodology in a new context and the potential uses and insights that this supports. This is done in the spirit of applied science to develop practical applications based on known tools or knowledge.

The resultant model represents a boundary object which we think helps stakeholders and experts to have structured conversations (Star and Griesemer 1989), in this case about the complex issue of farmer technology adoption. We recognise that the model here, whilst a refinement on previous attempts at describing innovation adoption by farmers, it is likely to be one iteration in an ongoing learning process (Locke 2007).

We also acknowledge that there are alternative models for describing technology adoption barriers and enablers amongst small-holder farmers; in particular the previously published ADOPT model (Kuehne, Llewellyn et al. 2011). The ADOPT model is an equation based model based on extensive research into the topic of technology adoption. The ADOPT model focuses on providing "*predictions of a practice's likely rate and peak level of adoption as well as estimating the importance of various factors influencing adoption*" (Kuehne et al., 2017, p.115) in the farming context. It considers four broad factors that influence the likely adoption of farming practices, i.e. population-specific influences on the ability to learn about the practice; learnability characteristics of the practice; relative advantage for the population; and relative advantage of the practice

Does the model described in this paper provide knowledge contribution that the ADOPT model didn't? We believe that the model described in this paper includes factors not included in the ADOPT model, has a different, yet to be proven, potential for being embedded into local practice, and importantly we believe that the model described in this paper is more transparent than the ADOPT model. The computational framework is different as is the empirical foundation. More importantly, we believe that diversity of approaches supports greater rates of innovation in this area.

## 5. Developing the Bayesian Network

Developing a Bayesian Network, in a purely computational sense, involves three steps (Neapolitan 2003): 1) Identify the variables that impact on the likelihood of technology adoption. 2) Identify the relationships between these variables. 3) Populate the Conditional Probability Tables (CPTs) with numbers after discretisation of variables.

When sufficient and adequate data is available, it is possible to complete these steps by means of algorithms for structure and parameter learning (Pollino, Woodberry et al. 2007), but philosophically it is yet to be proven that this is an effective way of building social science theory compared to for example Inductive Theory Building (Locke 2007). When data is limited or completely unavailable, computational structure and parameter learning of Bayesian Networks is not possible but models can instead be developed based on knowledge elicitation from experts (Castelletti and Soncini-Sessa 2007; Barton, Saloranta et al. 2008) or by using an existing theoretical basis for the model. When building a model based on elicited knowledge it is particularly important to deal with issues such as uncertainty and bias, subjectivity and representativeness of opinions (Krueger, Page et al. 2012).

It is also, for the purpose of increasing the chances of usefulness, desirable to ensure that potential users to the extent feasible understand and agree with the assumptions underlying the model, which ultimately is a representation of the collective understanding of a complex problem.

The purpose of the Bayesian Network model in this paper, is to enable ongoing social learning about the socio-technical innovation adoption processes amongst small-holder farmers, with a particular focus on the context of southern Laos; as well as to highlight differences in the representations of the innovation adoption process between different groups of stakeholders.

The modelling approach is also built on the acknowledgment that the processes of innovation adoption are multi-faceted, complex and largely hidden from our view, yet we recognise the epistemic construction of knowledge and believe that individual's representation of this process is based on their interactions with their physical and social environments, as per Dray et al (2006). Furthermore we acknowledge the importance of social learning in developing decision support systems, and how this can be mediated through boundary objects (such as conceptual models or BNs) in a participatory and iterative manner (Jakku and Thorburn 2010).

Taking into account limitations in terms of data availability and scope in terms of complexity of the socio-technical process of adoption, this study has embraced a Bayesian network modelling process, where the model in its various iterations is viewed as a boundary object to support social learning.

The starting point is a review of theoretical models of technology adoption, in acknowledgment that a large body of research exists on this topic. To support social learning and acceptance of assumptions, this conceptual model has been adapted to the context of small-holder farmers in Laos via iterations of expert and stakeholder feedback. Finally, once a conceptual was agreed on, surveys of experts and small-holder farmers were undertaken to provide quantification of parameters. The quantification of parameters embraced a dialectic approach, aligned with the thinking espoused by Fischer (2003), which acknowledges how the perspective on the process is social constructed and is based on lived experience and perspective, rather than perfect understanding of technology adoption. Therefore, we explore different perspectives on technology adoption, amongst different groups of stakeholders.

The process involves a series of steps (see Table 2) based on the following principles:

- Theory building based on knowledge of innovation adoption which is available in literature.
- Repeated rapid prototyping of a series of conceptual models used as boundary objects to support social learning
- Through interaction with the conceptual models, opportunities for expert scrutiny of model assumptions, providing iterations of refinement towards a point of universal expert consensus on the adequacy of the conceptual model.
- Surveys of different groups of stakeholders to enable a range of parameter estimates.

*Table 2: Research activities, functions and quality control*

| **Activity** | **Function** | **Quality control** |
|---|---|---|

| | | |
|---|---|---|
| Review literature on innovation adoption and build initial conceptual model | - Build on existing theories<br>- Create conceptual model | - Subsequent social learning and expert feedback |
| Using a series of updated conceptual models as boundary objects to seek feedback from experts and stakeholders | - Social learning<br>- Adapting existing theory to the study context | - Survey of experts to gauge their trust in the final conceptual model |
| Surveys of small-holder farmers and stakeholders/experts | - Parameterisation of final conceptual model | - Sensitivity analysis<br>- Dialectic exploration of different perspectives |

These steps are illustrated in Figure 1, demonstrating the process for developing the Bayesian Network:

1. **Theory as a starting point**: use of insights and theory from literature to create an initial conceptual model.
2. **Convergence towards a perceptual model**: Iterations between rapid prototyping and expert scrutiny of model assumptions. Eventually, these actions (usually) converge towards a Bayesian Network model that experts agree adequately describes the problem. However, this is primarily a perceptual model, the systematic structuring and qualitative understanding of the problem- for which CPTs need to be quantified by means of expert opinion.
3. **Quantification of probabilities**: Probabilities are quantified using a survey of expert opinion. This allows for the translation of the perceptual model into a formal model where mathematical parameters have been quantified.

4. **Application of model**: The formal mathematical model is then translated into a procedural model within the Netica software system, i.e., the computer implementation of the formal model.

The exploration of the model also involves sensitivity analysis to explore whether the model provides reasonable results, and to what extent different perspectives yield different results.

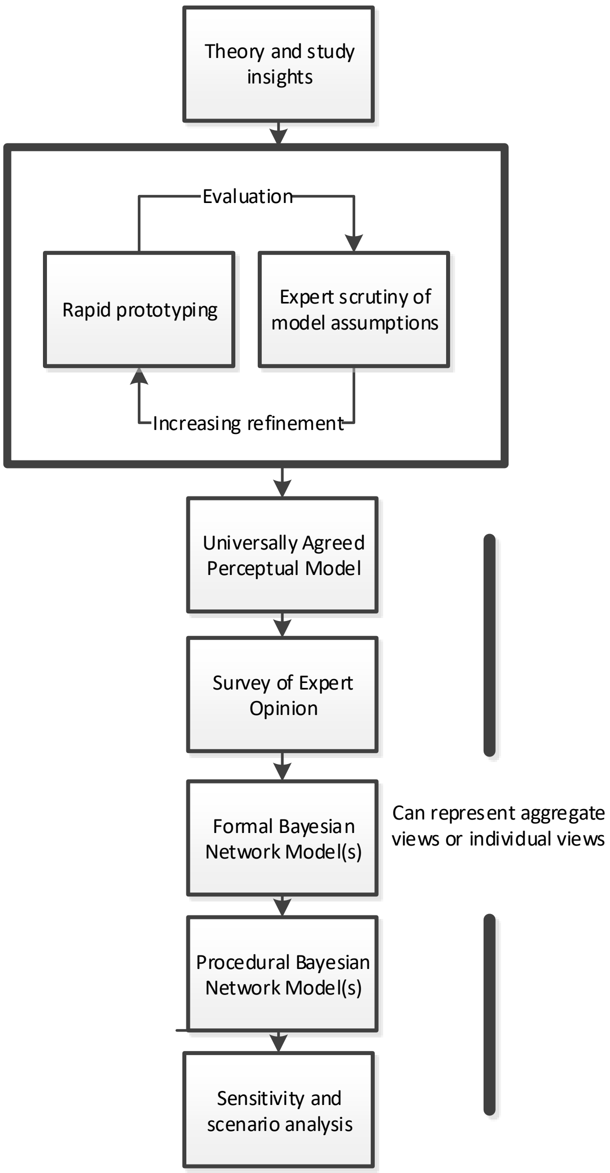


*Figure 1: Process adopted for developing the Bayesian Network*

## 5.1 Theory as a starting point

To initiate the model and develop an early prototype, factors and inter-relations between such factors are gleaned from the theory of technology adoption. In particular, we draw on the theory of planned behaviour, the Consumat model and the theory of technological transitions.

The theory of planned behaviour stipulates that behaviour is influenced by the intention to undertake a particular behaviour, such as adopting a technology, which in turn is largely influenced by three key factors:

1. A positive attitude towards the behaviour, on the basis of perceived benefits of undertaking the behaviour. This is referred to as the 'attitude'.
2. Whether an individual believes that 'significant others' would like them to carry out the behaviour. This is referred to as the subjective norm, a type of peer pressure.
3. Whether the individual has the confidence to carry out the behaviour resulting in the desired outcomes. This is referred to as the 'perceived behavioural control' and relates to capacity and confidence.

The Consumat model of technology adoption states that factors influencing adoption are based on fulfilling 'existential needs' relating to food, income, housing, etc.; as well as 'social needs' that relate to interactions among people, specifically belonging to a group and having a social status. Further, the Consumat model also considers that there is often a level of uncertainty and limited information when people make decisions and that in order to come to a decision in information-limited situations, people develop strategies that depend on the level of uncertainty and the level of their 'needs' satisfaction. The Consumat model framework relies on the following notions:

- Whilst people tend to seek to maximize 'needs' satisfaction, in both a social and existential way, when people are uncertain about outcomes of their decisions, as human cognition is inevitably limited, people develop heuristic rules on which they base their decisions.

- The types of heuristic rules that people adopt for making decisions are (depending on circumstances): to imitate, to inquire, to optimize or to repeat. Specifically, when people are satisfied but uncertain, they inquire. When they are satisfied and certain, they repeat. When they are unsatisfied but uncertain, they imitate, and when they are unsatisfied and certain, they optimize.

The theory of technological transitions, however, focuses on the interaction between multiple scales throughout the process of innovation and wider adoption of the innovation. The three key scales represent the following transitions (Geels 2002; Geels 2005; Geels and Schot 2007; Geels and Schot 2010):

- *Niche*: In limited contexts, an innovation may provide solutions for limited and contextual problems. These technologies evolving in specific niches may also emerge as possible solutions to mainstream problems.
- *Regime*: To support an innovation there is a requirement for links between actors and functions, for example, inter-linking of supply chains, regulation, and practices. Such regimes are important for optimal functioning and widespread adoption of an innovation. Technology regimes can be slow to develop.
- *Landscape*: High-level drivers for change, such as economic pressures, cultural values, social trends or environmental values, tend to assist the transition.

### 5.2 Convergence towards a perceptual model

Bayesian Network models can be developed quickly in the Netica software system (by the Norsys software corporation, http://www.norsys.com/netica.html). This is an easy-to-use and intuitive software environment for quickly developing Bayesian Network models. As the Netica software system provides the capability for quickly drawing up conceptual diagrams, this is a useful tool for creating boundary objects with which to engage with experts.

In fact, the rapid prototyping in Netica allows for the use interim conceptual models as boundary objects around which to structure interviews with experts. In particular, at this stage, it was important to embed the insights from the other components of the broader study, so other research team members were interviewed. These interviews were structured around, 1) **explaining the assumptions of the model**, i.e. the variables and linkages (i.e. nodes and arcs in the graphical conceptual model), 2) **invite critique**, i.e. ask whether the expert agrees with the assumptions of the model, 3) **invite suggestions for updates**, i.e. ask whether the expert if they would like to suggest any improvements to the model. In the experience of the senior author, this simple approach nearly always converges towards a model that experts can universally agree on.

**Workshop process**: After several conversations and model refinements, the adapted model structure was explored at a workshop with experts and stakeholders in Laos as is further described in the project report describing the BN development (Moglia, Alexander et al. 2017). The meeting was organized by local government staff and was held in Savannakhet city, Laos, on 28th July 2016 in the Provincial Agricultural and Forestry Offices. In addition to the research team, there were 20 participants in the workshop. There were 6 Provincial Agricultural and Forestry Officers, 5 District Agricultural and Forestry Office Managers, 4 District Agricultural and Forestry Office staff members, 2 District Governors (DGs) and 3 rice mill owners (private enterprises). All participants had experience and interest in smallholder farmers’ adoption of technologies. The workshop consisted of two sessions:

1. Training participants in probabilistic thinking and explaining the preliminary model to review and discuss. In this session, the process was to slowly build up the level of complexity by introducing probabilities, introduce BNs with a simple context-relevant example, introduce the components of the full model, and then to introduce the full BN model.

2. Reviewing and discussing the presented model,  in order to refine and improve. This was done in group sessions facilitated by the local team, where groups were chosen to represent particular perspectives. The model was reviewed and suggestions for changes and updates were used to modify the model.
3. Subsequently, several questions were directed at the group as follows:
    a. What factor is most likely to make farmers not adopt a specific technology? Multiple technologies were reviewed in this manner.
    b. In relation to the adoption of a technology, what factors influence this factor?
    c. What can you do to improve the chances of this factor not hindering adoption?

**Refinement of model based on workshop input**: This interview and subsequent workshop process helped identify a range of refinements of the model, as is described in the project report (Moglia, Alexander et al. 2017). For example, participants provided feedback that included discussions on how to embed the role of extension services as well as traders and access to market into the model (Moglia, Alexander et al. 2017). After adjusting the model based on workshop feedback, the perceptual model in Figure 2 was established. Note, in Figure 2, the squares represent factors and the arrows represent relationships between two factors, i.e., one factor influencing another. The tables within the boxes represent the discrete states of factors. The variables of the model and their discrete possible states are listed in Table 3. In this table, the factors of the model and their associated numbering are shown in column one, their description in column two, the discretisation in column three, and finally, the factors influencing this factor are shown in column four (numbers are as per column 1).

**Workshop participants' evaluation of the conceptual model**: After spending about 2 hours in facilitated in discussion of the model in detail, as well as exploring potential improvements; as part of the electronic voting survey of workshop participants, a question was put to the participants to respond via electronic voting system (Lumi, http://www.lumiglobal.com/): "*What is your impression of the diagram/model that you have explored in terms of its ability to describe what influences adoption by farmers?*" In response, 95% of participants chose the option "*The model requires some minor modifications in order to be appropriate*" whilst 5% responded, "*The model is perfect and covers everything that needs to be covered*". When asking the participants about the minor required modifications, they noted that this referred to what they had described in the previous facilitated session. ..

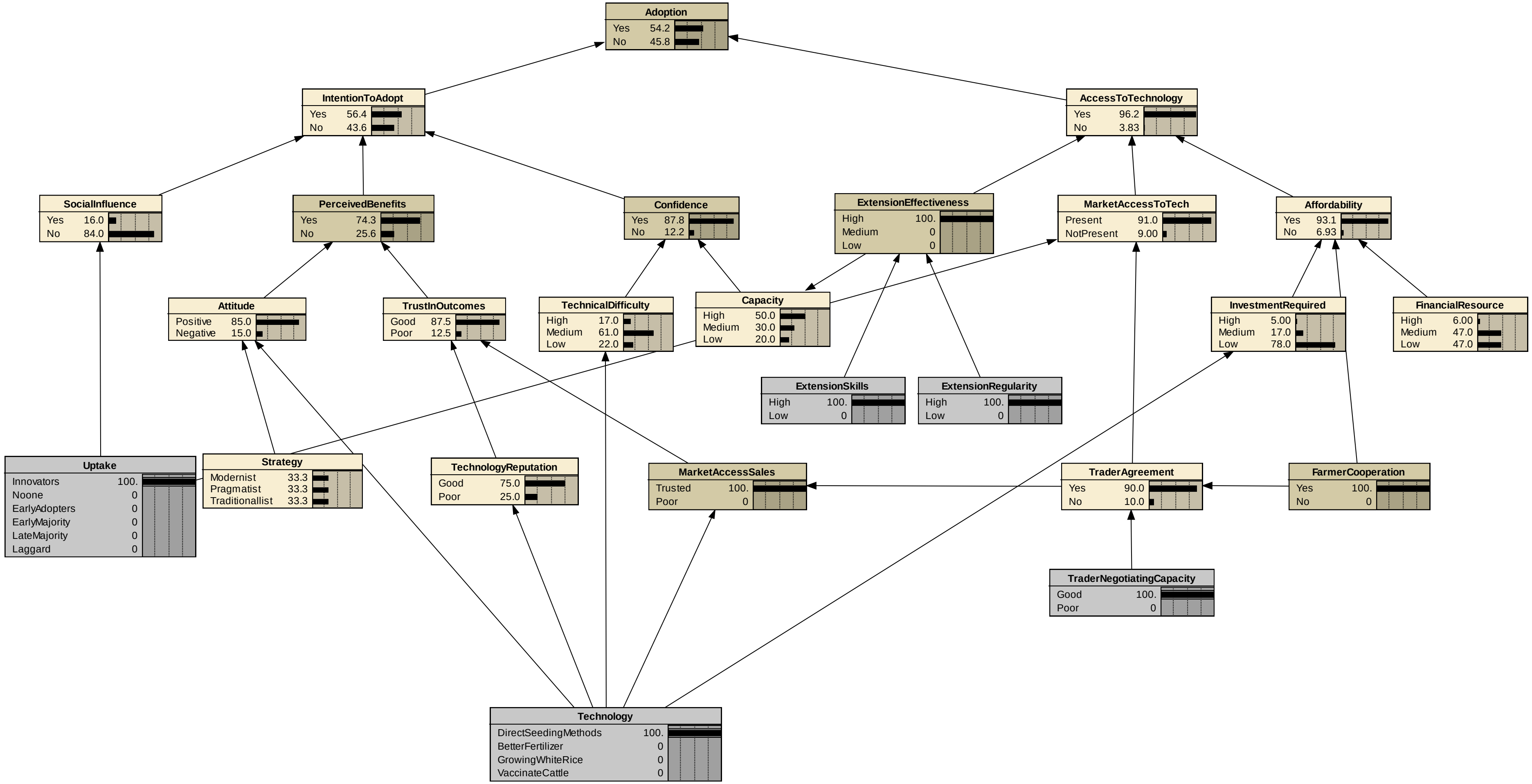


*Figure 2: Finalized BN model*

*Table 3: Model variables and their discrete states*

| **Factor** | **Description, i.e. measuring the:** | **Discrete states** | **Influencing factors** |
|---|---|---|---|
| 1. Adoption | Adoption of technology. | Yes; No | N/A |
| 2. Intention to adopt | The desire to adopt the technology. | Yes; No | 1 |
| 3. Access to technology | Ability to purchase or otherwise access the technology for adoption. | Yes; No | 1 |
| 4. Social influence | The tendency to be swayed by what other people do. | Yes; No | 2 |
| 5. Perceived benefits | Confidence that the technology will deliver benefits | Yes; No | 2 |
| 6. Confidence | Feeling that the adoption of the technology is something that the farmer can successfully do. | Yes; No | 2 |
| 7. Attitude | Perceived value vs the perceived cost of the technology, in a holistic sense. | Positive; Negative | 5 |
| 8. Trust in outcomes | Level of certainty that the technology can deliver promised benefits. | Good; Poor | 5 |
| 9. Technical difficulty | The difficulty of using the technology in a productive manner. | High; Medium; Low | 6 |
| 10. Capacity | Measuring the technical capacity of the farmer. | High; Medium; Low | 6 |
| 11. Extension effectiveness | The effectiveness of the extension workers in supporting farmers in the technology adoption process. | High; Medium; Low | 3, 10 |
| 12. Market access to technology | Level of commercial access to the technology from traders, or other means. | Yes; No | 3 |

| | | | |
|---|---|---|---|
| 13. Affordability | Whether the farmer can afford the technology. | Yes; No | 3 |
| 14. Investment required | Funds required for purchasing and operating the technology. | High; Medium; Low | 13 |
| 15. Financial resources | Amount of funds available to the household. | High; Medium; Low | 13 |
| 16. Extension skills | Skills of the extension workers. | High; Low | 11 |
| 17. Extension regularity | The regularity of extension workers getting out into the villages. | High; Low | 11 |
| 18. Uptake phase | The phase of the adoption process, as per Rogers (2003) | Innovators, early adopters, early majority, late majority, laggards. | 4 |
| 19. Farming strategy | Farmer strategy based on a typology (Alexander, Parry et al. 2018) | Modernist; Traditionalist | 7, 12 |
| 20. Technology reputation | The reputation of the technology, i.e. stories about outcomes. | Good; Poor | 8 |
| 21. Market access sales | Whether farmers know they can sell their produce at a good price. | Trusted; Poor | 8 |
| 22. Trader agreement | Agreements with traders about access to the market. | Yes; No | 21 |
| 23. Farmer cooperation | Farmer cooperation in negotiations and ensuring the quality of their produce. | Yes; No | 22, 13 |
| 24. Trader negotiating capacity | Trader ability to reach a constructive agreement with farmers as individuals and/or cooperatives. | Good; Poor | 22 |

### 5.3 Quantification of probabilities

The probabilities within the BN model were quantified based data from the Farmer Perception Survey with 427 participants in 10 villages in Savannakhet and 318 participants in 10 Champasak villages (Greenhalgh, Moglia et al. 2017) and data collected through a survey at a workshop (Moglia, Alexander et al. 2017). Both the household survey data and the workshop survey data was collected using the Lumi technology, a novel electronic voting system whereby participants, sitting together, used small handheld devices to indicate their response to survey questions projected onto a screen from a laptop computer.

The methodology for data collection via Lumi is according to a pre-prepared script and survey design developed by experienced social scientists to ensure clear and unambiguous language in the questions, as well as pilot testing to promote appropriateness to the socio-cultural context. The survey questions were entered onto a PowerPoint presentation displayed in front of the gathered crowd, and due to the sometimes limited literacy in the participants, read out aloud by the facilitator. Questions from survey participants were allowed, but the facilitator was under strict instruction to avoid, if possible, the introduction of bias. For the household survey, villagers were gathered by the “village head” with good crowds participating in each village. Much thought was also given to the choice of villages to survey, as there is considerable differences between villages. Statistical analysis shows a good cross-section of the village, but with some tendency for over-representation of women. For the workshop survey, a set of stakeholder perspectives were gathered, and so this was not a representative sample but a sample of important perspectives. Therefore, we explore the impact of these different perspectives in the sensitivity analysis of the BN model.

Whilst recognising that workshop data relates to opinions from experts and stakeholders, workshop data contributed to specifying the following: (1) technology reputation for the four types of technologies studied; (2) attitudes towards various technologies for different farmer types; (3) the technical difficulty of using the four target technologies; and (4) influences flowing into the intention to adopt. The numbers for the model are available in the technical report for the BN model (Moglia, Alexander et al. 2017) which is publically available in various databases online.

## 6. Turning the Bayesian Network model into information

The BN model can be used to explore what-if scenarios as well as to understand 'choke-points' in the adoption process. In other words, it can be used to explore such questions as: What are the factors that hold farmers back from adopting a technology? What actions can be carried out in order to increase adoption rates? What influence does the farmer 'type' have on the chances of adoption? To illustrate this functionality, the model can be used to evaluate peak adoption levels by exploring the probability of technology adoption as a function of the uptake phase as shown in Figure 3. The uptake phases (factor 18 in Table 3) are aligned with adopter category(Rogers 2003): 1) No one (0%), 2) Innovators (first 2.5%), 3) Early adopters (up to 16%), 4) Early majority (up to 50%), 5) Late majority (up to 84%), and 6) Laggards (up to 100%). This provides an estimate of the peak adoption level (i.e., the plateau level of the S-curve which is common in innovation diffusion theory as per Rogers, 2003). The peak adoption level is then estimated as the adoption rate in the later stages of the innovation diffusion curve, i.e., the probability of adoption at the Laggard uptake phase, as indicated in Table 4.

*Table 4: Peak adoption rates for assessed technologies*

| **Technology** | **Peak adoption rate** | **Discrepancy between adoption phases and estimated adoption rates** |
|---|---|---|
| Direct Seeding Machines | 54% | No |
| Improved fertilizer | 50% | No |
| Vaccinating cattle | 37% | Yes – likely plateau ~ 32% |
| Growing white rice | 24% | Yes – likely plateau ~ 19% |

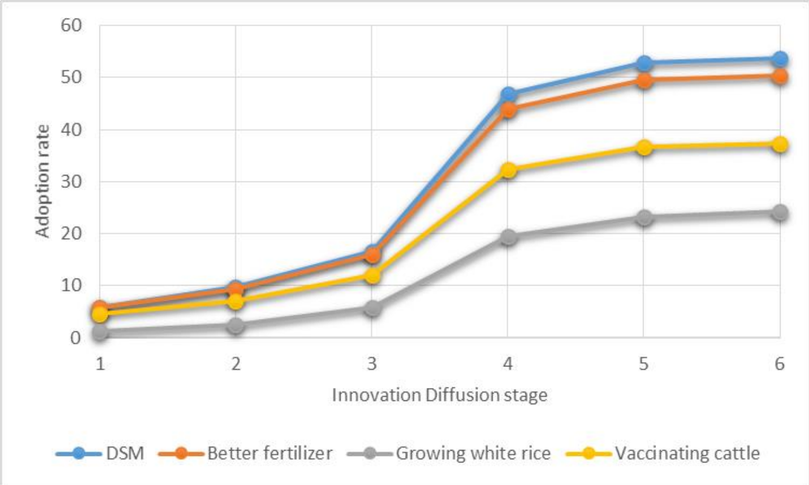


*Figure 3: Adoption likelihood in a given innovation diffusion stage*

The results in Table 4 represent the starting point of peak adoption rates in the baseline scenarios and without further efforts to increase adoption rates, and by applying the BN, it is quite plausible to identify the causes of lower than hoped for adoption rates:

- *White rice*: The exploration of the BN for growing white rice illustrates that the key choke point is the perceived benefits (factor 5 in Table 3), weighted down by a low trust in outcomes (factor 8 in Table 3), which in turn is weighted down by access to market for sales of the produce (factor 21 in Table 3). The model reflects anecdotal evidence from experts, expressing major difficulties. The key antidote to this issue, according to the model, is to ensure that there is an agreement between farmers and traders to allow access to markets. However, even with this is present there is only a 60% chance of being sure of farmers' access to markets to sell their produce. Thus, when such an agreement exists (90% probability), the peak adoption rate is still only 34%. This is a 42% improvement but still a relatively low overall adoption. Further inspection reveals that experts stated that growing white rice had a mixed reputation amongst farmers. For farmers to grow white rice at the scale they will require assurances of being able to sell the product, as well as requiring further promotion to farmers to improve the current and poor reputation of producing and selling white rice. As Lao people don't eat this variety of white rice, they cannot use it for home consumption should the markets fail.

- *Vaccination*: When undertaking a similar analysis of the vaccination of cattle, the weakest point is Intention to Adopt (factor 2 in Table 3) due to relatively low rates of Confidence (factor 6 in Table 3, also due to this being a relatively difficult technology to administer correctly (factor 9 in Table 3) and the commonly inadequate capacity of the farmers (factor 10 in Table 3) in this respect. Hence, when Extension Effectiveness (factor 11 in Table 3) is improved (one of the levers to mitigate low capacity) there are some immediate benefits in terms of higher intention to adopt (factor 2 in Table 3) and consequently a higher likelihood of adoption (factor 1 in Table 3).
- *Direct Seeding Machines*: the analysis shows that the weak point is again the Intention to Adopt (factor 2 in Table 3) due to relatively lower Confidence (6 in Table 3), and relatively lower Trust in Outcomes (factor 8 in Table 3). Hence, the best way to improve the adoption of Direct Seeding Machines, according to the model, is to support and teach farmers how to use machines correctly, as well as tackling the poor reputation of these machines (unsuitable to small paddy location, breakdown and maintenance issues, difficult to access, need for adaptation, etc.).
- *Improved Fertiliser*: the main issue is the often limited ability of the farmer to apply the technology correctly (Technical difficulty: factor 9 in Table 3), resulting in low Confidence in its application (factor 6 in Table 3). Thus, education of farmers appears to be the most effective way to improve Adoption of this technology (factor 1 in Table 3).

These examples show that the model, when applied to four different technologies, will generate insights on the factors that have the greatest influence on adoption rates. This is achieved by integrating the aggregation of expert knowledge within a framework built on theory, and subsequently extending by means of computational tools, inferences beyond what is possible by human cognitive faculties.

Another interesting result is that when exploring the peak adoption rate as a function of Farmer Strategy, i.e. to see to what extent these adoption curves are influenced by the types of farmers. This is important as research has indicated that farmers' motivations are highly dependent on farmers' viewpoints (Alexander, Larson et al. 2016). The influence of farmers' viewpoints is technology dependent, as shown in Table 5, where there is a significantly lower adoption rate for farmers with a traditionalist mindset. This effect was particularly pronounced for vaccinating cattle and the use of improved fertilizers, as additional production costs are incurred, perhaps without any perceived benefit.

*Table 5: Peak adoption rates as a function of farmer strategy*

| **Technology** | **Modernist (Labour saving)** | **Traditionalist (Traditional labour)** |
|---|---|---|
| Direct Seeding Machines | 56% | 50% |
| Improved fertilizer | 61% | 38% |
| Vaccinating cattle | 45% | 28% |
| Growing white rice | 27% | 23% |

**Note**: For descriptions of the farmer attitudes, i.e., modernist vs. traditionalist, refer to the recent paper from the same study on farmer attitudes as explored by using Q methodology (Alexander, Parry et al. 2018).

## 7. Sensitivity analysis and robustness of results

To evaluate the sensitivity of the model outcome (i.e. the likelihood of adoption) to parameter values, we use Netica functionality for sensitivity analysis, which provides the output as per Table 6 showing the factors that have the greatest influence on the likelihood of adoption. The mutual information measure is an indication of to what extent collecting information about variable X (say IntentionToAdopt) reduces the total uncertainty about variable Y (say Adoption). We can see, for example, that for white rice, the information about the IntentionToAdopt part of the Bayesian Network has a significantly greater impact on the likelihood to adopt than areas relating to

TrustInOutcomes or AccessToTechnology. The columns represent what percentage of the factors rely on mutual information for the difference practice change analyses.

*Table 6: Sensitivity analysis results, percent mutual information with adoption (likelihood) for different technologies*

| | **White rice** | **Vaccinating cattle** | **Direct Seeding Methods** | **Fertilizer** |
|---|---|---|---|---|
| Adoption | *100.0* | *100.0* | *100.0* | *100.0* |
| IntentionToAdopt | *77.5* | *55.6* | *68.8* | *62.5* |
| PerceivedBenefits | *32.8* | *15.3* | *19.2* | *15.7* |
| TrustInOutcomes | ***20.9*** | 6.4 | *10.1* | 3.4 |
| AccessToTechnology | *10.3* | ***23.1*** | *13.8* | ***17.9*** |
| MarketAccessSales | 6.8 | 0.0 | 4.1 | 0.0 |
| Attitude | 6.4 | 7.9 | 7.9 | ***11.7*** |
| TechnologyReputation | 5.7 | 3.9 | 6.4 | 2.2 |
| Affordability | 4.7 | ***12.7*** | 5.7 | 8.8 |
| Confidence | 3.2 | 7.2 | **9.8** | **9.6** |
| MarketAccessToTech | 3.0 | 2.5 | 4.1 | 3.7 |
| SocialInfluence | 2.9 | 1.5 | 1.6 | 1.5 |
| TraderAgreement | 2.8 | 1.6 | 2.7 | 2.4 |
| TechnicalDifficulty | 1.5 | 2.0 | 3.0 | 2.8 |
| FarmerStrategy | 0.8 | 1.6 | 0.3 | 2.4 |
| FinancialResource | 0.5 | 1.8 | 0.2 | 0.5 |
| Capacity | 0.5 | 3.4 | 4.2 | 4.3 |
| InvestmentRequired | 0.3 | 2.8 | 1.5 | 2.5 |
| ExtensionEffectiveness | 0.04 | 0.3 | 0.2 | 0.2 |
| AccessToFinance | 0.03 | 0.05 | 0.3 | 0.09 |
| ExtensionRegularity | 0.01 | 0.1 | 0.05 | 0.07 |
| ExtensionSkills | 0.001 | 0.01 | 0.006 | 0.008 |

We see in the Table 6 how the relative importance of factors varies depending on technology, and the table is in fact rather revealing about the types of factors which are particular barriers/enablers for the different practice-changes, although the table does not capture some of the non-linear effects (i.e. game changers like improved extension skills are not highlighted).

Furthermore, we can also explore, based on survey data collected during the workshop on perceptions of reputation of practices, technical difficulty, required affordability and attitudes towards the practice amongst different types of farmers, amongst the different types of perspectives, as well as to explore what this means in terms of perceived likely adoption of practices. As an example, see Figure 4, providing an illustration of the impact of different perspectives on the estimated likelihood of adopting the practice of growing white rice. Based on the small sample in the workshop, Entrepreneurs (i.e. mill owners etc.) generally believe that the practice is less difficult and more affordable than the other groups; whilst provincial and district officers have a much more negative expectation regarding the farmers' belief that the practice will achieve expected goals.

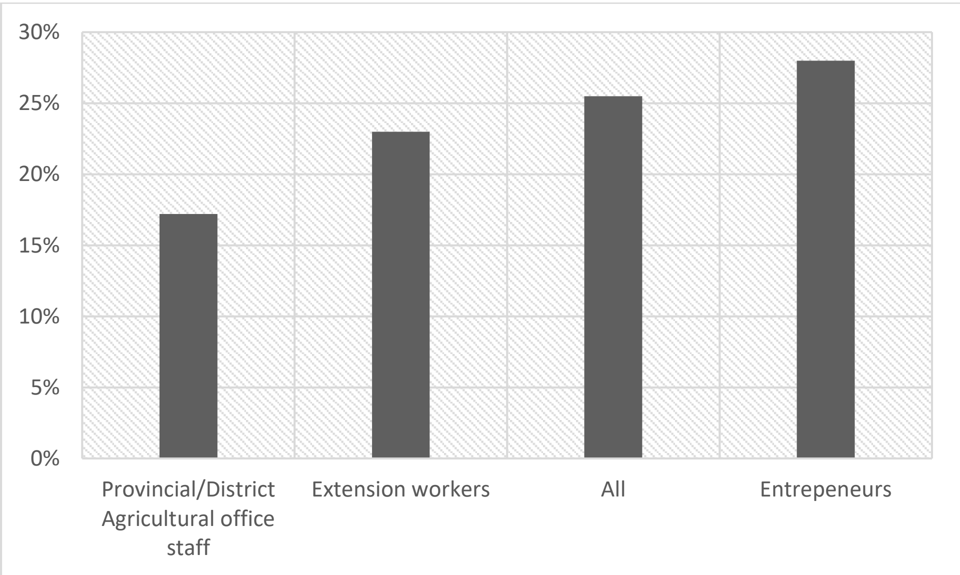


*Figure 4: Estimated (via BN) likelihood of adopting the practice of growing white rice, based on different group's perspectives*

These sensitivity analyses shows that the model is highly dependent on perceptions of key issues, and on many of these important factors, accurate data is currently unavailable. This highlights one of the first and perhaps more important uses of the model, i.e. to identify key data gaps where better data needs to be collected.

## 8. Discussion

This paper has shown that it is possible, with relative ease by researchers, to develop a BN model to describe the many factors that impact on the chances of a smallholder farmer adopting a technology to change his/her farming practice. The BN model has been developed as a way to synthesize findings from concurrent multi-disciplinary research activities. The BN model also provided a boundary object for valued experts and other stakeholders to engage with and provide assessments of the perceived technology adoption process. The model has been successful in highlighting specific barriers to adoption of several technologies and to provide suggestions on how to reduce the impact of these barriers. Furthermore, the BN model can be used by researchers, policy makers and extension workers, to focus on specific linkages and dependencies within the technology adoption process. The BN model and data can and should be adaptively updated using surveys, thus incorporating learning amongst experts on an ongoing basis. This approach is particularly useful in promoting social learning, i.e. supporting the collective understanding of adoption issues amongst a range of stakeholders and more specifically to evaluate and modify barriers to adoption. The potential use of the BN model and survey approach by field practitioners involves the ability to:

- Identify and discuss coordinated actions that may help increase adoption rates under different circumstances. Furthermore, these leverage points (i.e., actions that may help to increase adoption rates) are likely to be 'owned' by different stakeholders, so this approach assists in identifying potential strategies to be coordinated across multiple stakeholders, such as amongst traders, District Agricultural and Forestry Office Staff and Managers, rice millers, district governors, Provincial Agricultural and Forestry Officers (PAFO) and farmers.

- Evaluate the extent that different leverage points can improve the likelihood of technology uptake, and evaluate the most effective method to improve uptake. However, it should be noted that use of the model tends to illustrate that a coordinated and holistic plan is usually more effective than a more limited strategy, i.e. jointly triggering multiple leverage points tends to get better results than triggering single leverage points.
- Finding the key issues that are relevant to different technologies. In the current model, for example, we find that according to the model:
    - Being able to sell produce at a good price is critical for getting farmers to grow *white rice* and this is dependent on agreements between farmers and traders.
    - *Direct seeding methods* are likely to find traction with farmers, given time, but the main vulnerability for this technology is the reputation of the technology, and there is the potential of the farmer abandoning the technology if farmers are not able to use the technology effectively.
    - A key factor in relation to the use of *fertilizers* is financial capacity and access to buy the product from traders. When the technology is affordable and available, it is likely to be used at a reasonable rate by farmers, although whether it is appropriately applied is questionable and may vary depending on circumstance.
    - *Vaccination* of cattle is restrained by a number of factors, including somewhat limited perceived benefits and limited access to the technology (Moglia, Alexander et al. 2017).

To illustrate how the model can be used for sensitivity testing let us consider the introduction of an additional factor (suggested by the participants in the Savannakhet BN workshop), i.e., ‘improved extension’ as assessed in terms of the regularity of extension trips to villages, (factor 17 in Table 3) as well as improved skills of extension workers (factor 16). Systematically varying parameters and conditions in the model is important. For example, improving the variable- Extension Effectiveness (factor 11 in Table 3) – could be through increased funding for extension services from ‘limited funding' to 'regular funding' (i.e., giving extension workers the funding to allow more regular engagement with farmers). This action could double adoption rates in the 'early stages' of uptake for direct seeding methods, cattle vaccination and use of fertilizers. As with any modelling, there are implicit assumptions, and this result is also based on an underlying assumption of changing how extension services operate, i.e., assumptions on the impact of increased funding on Extension Effectiveness.

## 9. Strengths, limitations and enablers

**Strengths** of the approach in this paper are:

- The resultant BN model can be used to support stakeholders and experts in making collective assessments about adoption issues as well as to highlight differences in perceptions, hopefully prompting the collection of more robust data.
- The framework is suitable for describing probabilistic cause and effect relationships.
- The framework is good at incorporating a multitude of types of data into one coherent system of (probabilistic) logic.
- It is straightforward to incorporate a multitude of relevant issues and factors, including additional (late-comer) factors into the assessment.
- The approach highlights data gaps, and differences in perceptions, thereby making it apparent that further data is required.
- The Netica software environment for developing Bayesian Networks is attractive because it allows for easy changes to the model by a competent technician.
- The modelling capability can promote and support improved knowledge management and adaptive governance.

**Limitations** and **enablers** of the BN approach described here are:

- The requirement for mathematical skills and knowledge of the application of probability theory. This limitation can be overcome by building capacity in a small number of people with specialist roles. Several members of the Lao research team have shown an interest in developing specialized mathematical skills for ongoing use of the method.
- Stakeholders sometimes find it hard to conceptually grasp concepts like uncertainty and probabilities. This can be addressed through the use of metaphors, and by using examples such as those that involve rolling dice and/or gambling.
- To overcome the difficulty of application, it should be possible, to adapt the BN model and simplify construction for Lao colleagues by resorting to Excel spreadsheet, or similar relatively basic software environments.
- There could be role for a small number of experts who could support funding agencies, government departments, and other key agencies to use the modelling capability to undertake analysis to identify barriers and hurdles for individual technologies.
- There is currently only limited high quality data, and further improvements could be made (i.e. improved parameter quantification and structure learning) if the approach was embedded into a broader knowledge management and adaptive governance system.

## 10. Conclusions

This paper reports on the development of a Bayesian Network model for exploring the relative likelihood of technology adoption in the context of rice-based agricultural systems in southern Laos. To develop the Bayesian Network Model prototype, we have used concurrent research data and theoretical insights. The finalized BN model has been used to explore 'what-if 'scenarios and to understand 'choke-points' in the adoption process, as well as the impact of different perceptions of technology features The process of technology uptake for several technologies have been assessed: the use of direct seeding machines, growing Chinese variety white rice, using fertilizer and vaccinating cattle; all technologies potentially available to smallholder farmers. Adoption rates have been quantified, according to the farmers' production viewpoint, with lower than expected adoption results explained in detail. Improvements to the modelling tools would primarily involve collecting more robust data, and developing the knowledge management practices which together with the modelling capability can support adaptive governance.

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