# ATTITUDES OF EXTENSION AGENTS TOWARDS EXPERT SYSTEMS AS DECISION SUPPORT TOOLS IN THAILAND

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**Abstract of a thesis submitted in partial fulfilment of the requirements for the degree of PhD in Applied Management and Computing**

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**by S. Chetsumon**

It has been suggested 'expert systems' might have a significant role in the future through enabling many more people to access human experts. It is, therefore, important to understand how potential users interact with these computer systems. This study investigates the effect of extension agents' attitudes towards the features and use of an example expert system for rice disease diagnosis and management (POSOP). It also considers the effect of extension agents' personality traits and intelligence on their attitudes towards its use, and the agents' perception of control over using it. Answers to these questions lead to developing better systems and to increasing their adoption.

Using structural equation modelling, two models – the extension agents' perceived usefulness of POSOP, and their attitude towards the use of POSOP, were developed (Models ATU and ATP). Two of POSOP's features (its value as a decision support tool, and its user interface), two personality traits (Openness (O) and Extraversion (E)), and the agents' intelligence, proved to be significant, and were evaluated.

The agents' attitude towards POSOP's value had a substantial impact on their perceived usefulness and their attitude towards using it, and thus their intention to use POSOP. Their attitude towards POSOP's user interface also had an impact on their attitude towards its perceived usefulness, but had no impact on their attitude towards using it. However, the user interface did contribute to its value.

In Model ATU, neither Openness (O) nor Extraversion (E) had an impact on the agents' perceived usefulness indicating POSOP was considered useful regardless of the agents' personality background. However, Extraversion (E) had a negative impact on their intention to use POSOP in Model ATP indicating that 'introverted' agents had a clear intention to use POSOP relative to the 'extroverted' agents.

Extension agents' intelligence, in terms of their GPA, had neither an impact on their attitude, nor their subjective norm (expectation of 'others''beliefs), to the use of POSOP. It also had no association with any of the variables in both models.

Both models explain and predict that it is likely that the agents will use POSOP. However, the availability of computers, particularly their capacity, are likely to impede its use. Although the agents believed using POSOP would not be difficult, they still believed training would be beneficial.

To be a useful decision support tool, the expert system's value and user interface as well as its usefulness and ease of use, are all crucially important to the preliminary acceptance of a system. Most importantly, the users' problems and needs should be assessed and taken into account as a first priority in developing an expert system. Furthermore, the users should be involved in the system development.

The results emphasise that the use of an expert system is not only determined by the system's value and its user interface, but also the agents' perceived usefulness, and their attitude towards using it. In addition, the agents' perception of control over using it is also a significant factor. The results suggested improvements to the system's value and its user interface would increase its potential use, and also providing suitable computers, coupled with training, would encourage its use.

**Key words:** Attitudes; Extension; Expert Systems; Knowledge-Based Systems; Decision Support Systems; Personality Traits; Openness; Extraversion; Intelligence.

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# CHAPTER 1

# Introduction

> "Extension is an on-going process of getting useful information to people (the communication dimension) and then in assisting those people to acquire the necessary knowledge, skills and attitudes to utilise effectively this information or technology (the educational dimension). Generally, the goal of the extension process is to enable people to use these skills, knowledge, and information to improve their quality of life."
>
> (Swanson and Claar, 1984, p. 1).

The research reported in this thesis is about assessing the use and value of expert systems, a branch of artificial intelligence, as an extension aid. The research explores and concentrates on the human aspects of expert systems acceptance and use, and as such moves into exploring new concepts and theories.

This chapter introduces the background to agricultural extension in Thailand: the development of agricultural extension organisations, the functions and responsibilities of the Department of Agricultural Extension and its structure, the current agricultural extension approach. The research problem is then discussed – the potential place of expert systems, expert system use in Thailand, and theories of attitudes and intention. Finally, the research objectives, and their significance are presented.

## 1.1 The Background to Agricultural Extension in Thailand

Extension activities are widespread throughout the developing world and most governments have set up formally structured extension services to implement extension programmes and projects. The practice of extension is supported by personnel, budgets, offices and other resources (Oakley and Garforth, 1985).

The training and visit (T&V) system of agricultural extension, which is used in Thailand, is an approach fostering both close ties with research and the use by field staff of systematic routines. Extension agents attend monthly or fortnightly training programs on specific subjects; they then transfer the information to farmers on a regular schedule of frequent visits. A limited number of improved inputs and farming practices form the core of the extension message at any one time. As many agents as possible are recruited from among local farmers so that they have a practical understanding of local conditions, and 'contact farmers' are used to help disseminate the message to many more farmers than could otherwise be reached (Benor and Harrison, 1977; Benor and Baxter, 1984).

The T&V system has been introduced to most of India, Indonesia, and Thailand, and in many other countries in Asia. The application of its principles has been extended to several countries in Africa, Latin America and other parts of the world (Yudelman, 1984). The purpose of the T&V system is to build an effective professional extension service that is capable of assisting farmers to raise production, increase their income, and to provide appropriate support for agricultural development (Benor and Baxter, 1984).

A basic question is how the use of expert systems might be integrated into this T&V approach. Will extension agents find them useful and valuable?

### 1.1.1 The Development of Agricultural Extension Organisations

In Third World countries, the development of agricultural extension organisations took place mainly after the Second World War. In Latin America and the Caribbean, most of the national agricultural extension organisations were started in the mid-1950s, with a few established in the late-1940s, and others initiated in the early-1960s. The development of agricultural extension organisations in Asia and Oceania was similar to Latin America and the Caribbean, except that the midpoint was around 1960, with some of these organisations not starting until the 1970s. The establishment of agricultural extension organisations in African nations was somewhat later, with most extension organisations starting in the 1960s and 1970s (Swanson and Rassi, 1981).

As with other countries in Asia, in Thailand the national agricultural extension organisation was initiated around 1960. The Department of Agricultural Extension (DOAE) was established by a Royal decree (published in the government Gazette special issue of October 20, 1967) as an organisation under the Ministry of Agriculture and Cooperatives (MOAC) (Appendix A). This reorganised the administrative pattern of the Ministry and made the DOAE directly responsible for establishing and implementing a comprehensive agricultural extension program (http://www.doae.go.th/English/doaeeng2.htm, 1999).

### 1.1.2 The Functions and Responsibilities of the Department of Agricultural Extension

The DOAE has been asked to develop, promote, and transfer knowledge and technology on crop production and agribusiness to farmers; promote and enhance the formation of farmers' groups to obtain and disseminate agricultural information; and carry out other activities as specified in the Act or as assigned by the Ministry of Agriculture and Cooperatives, or the cabinet.

The ultimate goal of agricultural extension is to help raise farm income and upgrade the rural standard of living, which results in the stability of the economy and society as a whole. To enhance stable farm occupations and improve the quality of rural life in both economic and social terms, the DOAE listed its objectives as follows:

(1) To give ideas to farmers so that they can engage in their occupations in line with the natural environment, biology, production technology, economics, social, cultural, and political aspects of rural production.

(2) To serve as a means of transferring agricultural knowledge and technology from research institutions and other technical sources to farm populations, while taking into account field problems which must be resolved.

(3) To promote production of agricultural commodities for local and national consumption, agro-industrial use, and export.

(4) To provide services and subsidised production inputs for farmers on occasions such as natural disasters; serious plant disease outbreaks and where farmers are not able to help themselves. This objective is intended to ensure continuous farm productivity.

(5) To promote and encourage farm families to form farmer institutions and production groups, in order to ensure cooperative participation in the use of production technology, improved selection of type, quantity and quality of products, and to use groups as a base for marketing and the fair distribution of income.

(6) To cooperate with other agencies in the Ministry of Agriculture and Cooperatives in disseminating technical knowledge on crop production, livestock, fisheries, and forestry at the farm level; and cooperate with relevant government agencies and the private

sector in promoting agricultural development for the benefit of farmers and the country (http://www.doae.go.th/english/doaeeng3.htm, 1999).

In almost all these functions expert systems might potentially be useful. It was not possible to consider all these roles, so the research concentrates largely on how extension agents' attitudes towards an expert system's features, how their personality traits and intelligence, and how their perception of their control over using the system all influence their attitude towards its use.

### 1.1.3 The Structure of the Department of Agricultural Extension

To consider how expert systems could be used it is useful to consider the administrative structure of the DOAE (Appendix B). The Act establishing DOAE' s gave rise to the following administrative organisations:

**1.1.3.1 A Central Administration** consisting of a main office with 12 divisions, 6 regional agricultural extension offices (RAEOs), and 4 offices set up internally (http://www.doae.go.th/english/doaeeng5.htm, 1999).

The 6 RAEOs, namely Central RAEO located in Chainat province, Western RAEO located in Ratchaburi province, Eastern RAEO located in Rayong province, Northeastern RAEO located in Khon Kaen province, Northern RAEO located in Chiang Mai province, and Southern RAEO located in Songkhla province, are each equivalent to a division.

The functions of the RAEOs are to study and draw up plans and provide coordination in the context of crop production promotion, agri-business and farmers' institutions in their areas of responsibility; transfer technical know-how to provincial and district agricultural extension offices; promote, support, and supervise the works of the operating units which are attached to the regional offices such as the Seed Center, Horticultural Crop Propagation and Promotion Center, Sericultural Extension Center, Farm Mechanisation Center, Sugarcane Pest Control Center, and the Beekeeping Center (http://www.doae.go.th/english/doaeeng22.htm, 1999).

**1.1.3.2 A Provincial Administration** consisting of 76 provincial agricultural extension offices (PAEOs) (http://www.doae.go.th/english/doaeeng5.htm, 1999), 811 district agricultural extension offices (DAEOs), and 4,666 agricultural extension officers at sub-district levels (http://www.doae.go.th/stat/statt.htm, 1999).

The functions of PAEOs are to promote crop production, agri-business and good management of farmers' institutions; supervise and provide support to district agricultural extension offices, and coordinate agricultural development in the province (http://www.doae.go.th/english/doaeeng24.htm, 1999).

The functions of DAEOs are to carry out agricultural extension activities at the field level and represent the Ministry of Agriculture and Cooperatives at the sub-district level (http://www.doae.go.th/english/doaeeng25.htm, 1999).

There is, clearly, a well formed administrative structure which could facilitate the use and dissemination of expert systems.

### 1.1.4 The Current Agricultural Extension Approach

As an agricultural country with 22-26 % of agricultural goods exported (Table 1.1), and half of the population and labour force engaged in agriculture (Table 1.2), Thailand must develop her agricultural sector, especially the integration and cooperation between research institutions, agricultural credit organisations, production inputs groups, marketing organisations, and other relevant agencies, in order to strengthen the production efficiency of farmers.

Since the current situation of agricultural production and marketing, as well as the economic and social aspects of the farm population, have undergone considerable change from subsistence farming to commercial production and to export, it is necessary to adjust the agricultural extension approach in line with such changing circumstances. The operational and supporting systems were set up in 1994 and later modified to begin a new system on 1 January 1997. The general principle of the current agricultural extension system focuses on (1) human resource development both for extension personnel, farmers, farmers' spouses, and young farmers; (2) utilisation of appropriate technology; (3)

empowering regional and provincial offices to have more responsibilities; and (4) closer coordination among government agencies, the private sectors and local organisations (http://www.doae.go.th/english/doaeeng4.htm, 1999).

**Table 1.1** Values of agricultural goods exported between 1998 and 2004.

| Year | Values of Agricutural goods (Millions of Baht)# | Values of All Goods (Millions of Baht)# | Agricultural Goods Export (%) |
|---|---|---|---|
| **1998** | 591,062.08 | 2,248,776.30 | 26.28 |
| **1999** | 555,782.54 | 2,215,179.59 | 25.09 |
| **2000** | 626,286.05 | 2,768,064.76 | 22.63 |
| **2001** | 685,148.35 | 2,884,703.89 | 23.75 |
| **2002** | 694,402.74 | 2,923,941.37 | 23.75 |
| **2003** | 804,280.93 | 3,326,014.52 | 24.18 |
| **2004** | 882,954.80 | 3,922,410.54 | 22.51 |

# 1 Baht = $US 0.025

**Source**: Office of Agricultural Economics with the cooperation of the Customs Department, (adapted from http://www.oae.go.th/statistic/export/1301Vul-GO.xls and http://www.oae.go.th/statistic/export/1301Vul-W.xls, 2005).

**Table 1.2** Population and labour force in agricultural and non-agricultural sectors.

| Sector | Population | | Labour Force | |
|---|---|---|---|---|
| | Number (Million) | Percent | Number (Million) | Percent |
| **Agricultural** | 35.37 | 54.85 | 18.95 | 51.63 |
| **Non-agricultural** | 29.11 | 45.15 | 17.75 | 48.37 |
| **Total** | 64.48 | 100 | 36.70 | 100 |

**Source**: Office of Agricultural Economics (http://www.oae.go.th/AgriStruct.php, 2003)

## 1.2 Research Problem

### 1.2.1 The Potential Place of Expert Systems

Agricultural production has evolved into a complex business. It requires the accumulation and integration of knowledge and information from many diverse resources including marketing, production management and processing technology, disease, insect, pest, and weed management to name some examples. However, integrating and interpreting information from a large number of sources puts major intellectual demands on individual extension agents so that making use of agricultural and other specialists or experts is desirable. Unfortunately, the availability of these specialists is becoming relatively scarce in Thailand, due to both the early retirement policy imposed by the $8^{th}$ (1997-2001) and the $9^{th}$ (2002-2006) National Economic and Social Development Plan (http://www.infonews.co.th/CSC/detail.htm, 1999; http://www.infonews.co.th/CSC/ june7.htm, 1999; http://www.businessworld/ocsc.go.th/web/MainLink1.asp, 2004) and budget cuts after the economic crisis in July 1997. To alleviate these problems, expert systems have been identified as a useful tool with extensive potential as a more cost-effective means of extension program delivery (Gum and Blank, 1990), as an effective training tool in agricultural extension program (Rafea and Shaalan, 1996), and for technology transfer in extension services (Rafea, 1998), particularly, when supported by generalist extension officers, as in Thailand. Furthermore, the cost-performance ratio of microchips has been improving. This leads to a sharp decline in computer hardware and a dramatic increase in its performance (processing capacity and speed, memory, and so on) (Turban, McLean and Wetherbe, 2004). The role of expert systems as artificial experts becomes obvious. It is unlikely that a computer program can ever completely replace a human expert, but if an expert is unavailable and a problem needs to be solved, then expert systems may offer the best alternative (Plant and Stone, 1991).

Knowledge-based expert systems provide opportunities to increase the production management knowledge of all extension agents, regardless of background and training (Sullivan and Ooms, 1990). The effectiveness and impact of expert systems on human resource development was studied at the Central Lab for Agricultural Expert Systems in Egypt (Rafea and Shaalan, 1996), by comparing the performance of extension agents before and after a training course on the use of expert systems. Eleven extension agents specialised in protected cultivation and eight extension agents specialised in horticulture participated in the experiment. Sets of cases covering the different aspects of an expert system for managing cucumber production under plastic tunnels consisting of two subsystems, agricultural practice management, and disorder diagnosis and treatment (CUPTEX), and an expert system for managing orange production consisting of three subsystems, site assessment, agricultural practice management, and disorder diagnosis and treatment (CITEX) were prepared and distributed to the participants before training. The participants were asked to give their decisions on an irrigation schedule, a fertilisation schedule, and symptoms to be observed if a disorder is suspected, and a treatment schedule. After the participants had submitted their solved cases, training on the use of expert systems was conducted. The same sets of cases were distributed again and then evaluated. The results for both CUPTEX and CITEX were summarised in Table 1.3.

**Table 1.3** Performance enhancement of extension agents before and after using CUPTEX and CITEX.

| | **CUPTEX (Average score %)** | | **CITEX (Average score %)** | | **CUPTEX (% of enhancement)*** | **CITEX (% of enhancement)*** |
|---|---|---|---|---|---|---|
| | **Before** | **After** | **Before** | **After** | | |
| **Irrigation** | 40.00 | 72.40 | 35.50 | 64.05 | 81.0 | 84.14 |
| **Fertilisation** | 25.64 | 66.00 | 51.43 | 67.78 | 157.41 | 35.89 |
| **Verification** | 29.90 | 52.23 | 3.55 | 55.53 | 80.06 | 1464.08 |
| **Treatment** | 25.70 | 48.43 | 8.05 | 59.60 | 90.66 | 734.61 |
| **Average** | **30.31** | **59.77** | **27.13** | **61.74** | **102.28** | **579.18** |

* % of enhancement = Enhancement/Average score before using the expert system x 100 where the Enhancement is the difference between the average before and after using the expert system.

**Source:** Rafea and Shaalan (1996), p. 348.

The best enhancement for CUPTEX was in the fertilisation subsystem, whereas the best enhancements for CITEX were in the verification and treatment subsystems. The performance of the CITEX trainees on the verification and treatment subsystems increased dramatically (734.61 and 1464.08). This was because the performance of the CITEX trainees before using CITEX was very low (3.55 and 8.05). Rafea and Shaalan (1996) concluded that the expert systems could be an effective training tool in agricultural extension programs. The performance enhancement of extension agents was developed in a very short time after using the expert systems. The overall performance enhancement of CUPTEX extension agents was approximately 100% and the overall performance of CITEX extension agents was approximately 580% (Rafea and Shaalan, 1996).

However, whether expert systems will be accepted by the Thai extension agents, and provide real value, is not known. There may be several factors, both the systems themselves and the extension agents' characteristics, influencing the acceptance of the systems. Clearly, the confidence of the extension agents in the systems' ability to provide accurate and reliable advice, and other resource and technical support are crucially important in the adoption or rejection of the systems. The extension agents' personal characteristics, such as their attitudes towards the features of the systems, and towards the use of the systems as decision support tools, their personality traits, as well as their intelligence might all be equally important to the adoption or rejection of the systems.

### 1.2.2 The Place of Expert Systems in Information Technology Support Systems

Information technology support systems are rapidly evolving over the past decade. Traditional information systems are categorised into 5 systems: transaction processing systems (TPS), management information systems (MIS), decision support systems (DSS), group support systems (GSS), expert systems (ES), and executive support systems (EES). However, the usefulness of this classification is quickly losing its value as most current information systems incorporate more than one system. In this classification, expert systems are regarded as an extension to decision support systems (Thomson and Cats-Baril, 2003).

Decision support systems mean different things to different people. There is no universally accepted definition of decision support systems. Recently, Whitten, Bentley and Dittman (2004, p. 12) have broadly defined a decision support system as "an information system that either helps to identify decision-making opportunities or provides information to help make decisions." And Turban, McLean and Wetherbe (2004) have classified information technology support systems based on the type of support provided (Table 1.4) and have defined a decision support system as "a computer-based in formation system that combines models and data in an attempt to solve semi-structured and some unstructured problems with extensive user involvement." (Turban, McLean and Wetherbe, 2004, p. 550).

**Table 1.4** Main types of IT support systems.

| System | Employees supported | Description |
|---|---|---|
| Transaction processing system (TPS) | All employees | Processes an organization's basic business transaction (e.g., purchasing, billing, payroll). |
| Management information system (MIS) | All employees | Provides routine information for planning, organising, and controlling operations in functional areas. |
| Office automation system (OAS) | Office workers | Increase productivity of office workers; includes word processing. |
| Word processing system | Office workers | Help create, edit, format, distribute and print documents. |
| Computer-aided design/Computer-aided manufacturing (CAD/CAM) | Engineers, draftspeople | Allow engineers to design and test prototypes; transfers specifications to manufacturing. |
| Communication and collaboration systems (e.g., e-mail, voice mail, call centres, others) | All employees | Enable employees and customers to interact and work together more efficiently. |
| Desktop publishing system | Office workers | Combines text, photos, graphics to produce professional-quality documents. |
| Document management system (DMS) | Office workers | Automates flow of electronic documents. |

**Table 1.4** Main types of IT support systems (cont.).

| | | |
|---|---|---|
| Decision support system (DSS) | Decision makers, managers | Combines models and data to solve semi-structured problems with extensive user involvement. |
| Executive support system (ESS) | Executives, senior managers | Supports decisions of top managers. |
| Group support system (GSS) | People working in groups | Supports working processes of groups of people (including those in different locations). |
| Expert system (ES) | Knowledge workers, non-experts | Provides stored knowledge of experts to non-experts and decision recommendations based on built-in expertise. |
| Knowledge work system (KWS) | Managers, knowledge workers | Support the gathering, organising, and use of an organisation's knowledge. |
| Neural network, case-based reasoning | Knowledge workers, professionals | Learned from historical cases, even with vague or incomplete information. |
| Data warehouse | Managers knowledge workers | Stores huge amounts of data that can be easily accessed and manipulated for decision support. |
| Business intelligence | Decision makers, managers | Gathers and uses large amounts of data for analysis by DSS, ESS, and intelligent systems. |
| Mobile computing systems | Mobile employees | Support employees who work with customers or business partners outside the physical boundaries of the organization. |

**Source**: Turban, McLean and Wetherbe (2004), p. 54.

Although expert systems are thought of as new decision support tools that have a potential to help improve extension agents' decision-making in Thailand, the following questions need to be answered before conducting the research:

(1) Is there any agricultural expert system in use by extension agents in Thailand?
(2) What are the decision problems faced by the agents?
(3) What are the sources of information currently used by the agents for their decision support work, and their usefulness?
(4) What type of information actually used by the agents for their decision support work, comes from experts from a range of fields?

Answers to these questions will provide necessary information for decision support for research planning.

### 1.2.3 Expert System Use in Thailand

It is clear, from a literature review, that agricultural expert systems in Thailand hardly exist. The two that appear are ESIM, an expert system for making decisions on water management in an irrigation management problem of the Mae-Taeng irrigation project in northern Thailand (Srinivasan, Engel and Paudyal, 1991), and an expert system for mechanical harvesting and transportation of sugarcane (Singh and Pathak, 1994). Both are not appropriate targets for this research as they are not designed to meet the needs of extension agents. Furthermore, the review revealed not enough information is available to answer the last three questions. As extension agents' problems and needs are the first priority to be taken into account in this research, a preliminary mail survey and personal interviews (Appendix C) were conducted between December 1999 and February 2000 to gather the information needed. This information indicates the decision problems faced by the agents and the problem areas that expert systems can potentially help alleviate.

From the survey and interviews, it was clear that disease diagnosis is a common problem faced by the agents (Appendix D, Table D1). Sources of information currently used by the agents were ranked according to their usefulness scores. From the survey, an expert was ranked third, among ten sources of information, after textbooks and peers (Appendix D, Table D1.1). Similarly, from the interviews, experts were ranked second from among eleven sources of information, after their own experience (Appendix D, Table D1.2). This indicates the importance of experts as a useful source of information.

Although none of the interviewees had seen, or heard about, expert systems before being interviewed, they largely believed that the systems had a place in agricultural decision-making (score of 4.04), and had potential to help them as a decision support tool (score of 4.13) (where 1 = very little and 5 = very much). This might be due to the demonstration of an expert system (Drench) (Nuthall and Bishop-Hurley, 1996a; Nuthall and Bishop-Hurley, 1996b) during the interview sessions. In the mail survey, about 12% of the respondents had seen or heard about the systems before. However, they believed the systems had both a place in agricultural decision-making, and a potential to help them as decision support tools, with scores of 3.38 and 3.68 respectively. This might be due to lack of interacting with a real expert system.

Given these beliefs, and as rice is a crucial component of Thai agriculture, an example expert system for rice disease diagnosis and management (POSOP, named after the Goddess of rice in Thailand) (Chetsumon and Nuthall, 2002) was developed to test the extension agents' attitudes towards the use of an expert system as a decision support tool. Rice is the biggest contributor to gross domestic product (GDP) (25-36% of GDP from crops) (Table 1.5), and it is an important export good (10-15% of agricultural goods exported) (Table 1.6). Furthermore, rice makes up 51% of total agricultural area (Table 1.7), and is the most important of the economic crops (Table 1.8)

### 1.2.4 Theories of Attitudes and Intention

This study proposes a model of attitudes of extension agents towards the use of an expert system. Since the use of expert systems may not be entirely under the agents (volitional) control, the proposed theory and operational model is based on the Theory of Planned Behaviour (TPB) (Ajzen, 1985; 1987; 1988; 1991; http://www-unix.oit.umass.edu/~aizen/tpb/diag.html, 2002), together with Costa and McCrae' s (1992b) OCEAN model of personality traits, and Sternberg's (1985; 1988) Triarchic Theory of Intelligence. Extension agents' attitudes towards the use of POSOP might imply adoption or rejection of an innovation by extension agents. Thus, the work looks at some of the basic characteristics of extension agents and relates these factors to operational actions. Success in developing an explanatory model should have a major impact on future developments, as it will indicate the structure that expert systems should take to be useful and successful.

**Table 1.5** Gross domestic product (GDP) from crops at current market prices (Millions of Baht).#

| | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 |
|---|---|---|---|---|---|---|---|---|
| **Rice** | 53,086 | 63,109 | 82,966 | 98,261 | 117,542 | 83,353 | 81,130 | 83,672 |
| **Cassava** | 9,801 | 14,734 | 11,534 | 8,189 | 15,906 | 7,981 | 6,159 | 7,666 |
| **Cotton and Kapok** | 1,184 | 1,557 | 1,047 | 737 | 843 | 491 | 763 | 549 |
| **Kenaf and Jute** | 555 | 784 | 801 | 395 | 175 | 192 | 211 | 386 |
| **Tobacco** | 1,580 | 1,295 | 1,840 | 2,175 | 2,112 | 2,261 | 1,609 | 1,896 |
| **Sugarcane** | 13,849 | 17,161 | 19,506 | 20,408 | 16,939 | 18,771 | 19,065 | 18,171 |
| **Maize** | 6,248 | 10,292 | 11,638 | 8,598 | 9,316 | 9,991 | 9,429 | 10,027 |
| **Other Field Crops** | 5,325 | 5,579 | 6,506 | 6,352 | 7,060 | 5,481 | 5,919 | 6,522 |
| **Fruits** | 29,298 | 33,368 | 39,638 | 44,809 | 42,004 | 40,678 | 41,764 | 41,255 |
| **Vegetables** | 26,915 | 29,717 | 36,872 | 31,455 | 37,968 | 34,679 | 36,454 | 49,791 |
| **Coconut** | 3,124 | 2,351 | 3,402 | 2,685 | 4,166 | 5,547 | 1,986 | 2,001 |
| **Palm Bean** | 4,397 | 6,597 | 7,281 | 7,276 | 11,062 | 8,072 | 5,037 | 5,028 |
| **Coffee Bean, Tea Leaf and Cocoa Bean** | 2,399 | 3,326 | 2,455 | 2,458 | 3,960 | 2,442 | 2,602 | 715 |
| **Rubber** | 38,107 | 56,639 | 54,095 | 47,901 | 50,955 | 36,338 | 47,286 | 48,402 |
| **Other Crops** | 3,665 | 4,048 | 4,901 | 6,112 | 6,853 | 6,685 | 7,745 | 7,519 |
| **Total Value Added** | **199,533** | **250,557** | **284,482** | **287,811** | **326,861** | **262,962** | **267,159** | **283,600** |
| **Rice %** | **26.61** | **25.19** | **29.16** | **34.14** | **35.96** | **31.70** | **30.37** | **29.50** |

#1 Baht = $US 0.025

**Source**: National Economic and Social Development Board (adapted from http://www.nesdb.go.th/Main_menu/macro/gdp_data/reportagdp.asp?heading_id=18, 2003).

**Table 1.6** Value of rice and agricultural goods exported between 1998 and 2004.

| Year | Value of Rice (Millions of Baht)# | Value of Agricutural goods (Millions of Baht)# | Rice Export (%) |
|---|---|---|---|
| **1998** | 86,805.34 | 591,062.08 | 14.69 |
| **1999** | 73,810.42 | 555,782.54 | 13.28 |
| **2000** | 65,516.28 | 626,286.05 | 10.46 |
| **2001** | 70,165.28 | 685,148.35 | 10.24 |
| **2002** | 70,064.61 | 694,402.74 | 10.09 |
| **2003** | 76,699.16 | 804,280.93 | 9.54 |
| **2004** | 108,393.25 | 882,954.80 | 12.28 |

# 1 Baht = $US 0.025

**Source**: Office of Agricultural Economics with the cooperation of the Customs Department (adapted from http://www.oae.go.th/statistic/export/1301RI.xls and http://www.oae.go.th/statistic/export/1301Vul-GO.xls, 2005)

**Table 1.7** Land use in agriculture.

| Types of Areas | Area (Millions of Rai*) | Percent |
|---|---|---|
| **Rice** | 66.82 | 51 |
| **Field crops** | 31.44 | 24 |
| **Fruit trees** | 22.27 | 17 |
| **Residential and others** | 10.48 | 8 |
| **Total** | 131.01 | 100 |

*1 Rai = 0.16ha.

**Source**: Office of Agricultural Economics (http://www.oae.go.th/AgriStruct.php, 2003)

**Table 1.8** Production areas of important economic crops between 1989/90 and 1999/00.

| **Production Areas (Millions of Rai*)** | **1989/90** | **1990/91** | **1991/92** | **1992/93** | **1993/94** | **1994/95** | **1995/96** | **1996/97** | **1997/98** | **1998/99** | **1999/00** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **1. Rice** | | | | | | | | | | | |
| **1.1 in-season rice** | 59.195 | 58.205 | 55.177 | 56.295 | 56.153 | 56.373 | 57.407 | 57.291 | 57.172 | 57.918 | 57.195 |
| **1.2 off-season rice** | 5.306 | 5.244 | 3.705 | 4.494 | 4.158 | 3.098 | 4.304 | 5.946 | 6.437 | 7.231 | 6.459 |
| **2. Maize** | 11.165 | 10.910 | 9.219 | 8.446 | 8.370 | 8.829 | 8.346 | 8.665 | 8.729 | 9.184 | 8.452 |
| **3. Cassava** | 10.136 | 9.562 | 9.323 | 9.323 | 9.100 | 8.817 | 8.093 | 7.885 | 7.907 | 6.527 | 6.659 |
| **4. Sugar cane** | 4.298 | 4.929 | 5.791 | 6.267 | 5.355 | 5.887 | 6.279 | 6.314 | 6.172 | 6.004 | 5.865 |
| **5. Rubber** | 10.899 | 10.961 | 11.022 | 11.124 | 11.213 | 11.308 | 11.376 | 11.444 | 9.548 | 9.595 | 9.676 |

* 1 Rai = 0.16ha.

**Source**: National Economic and Social Development Board (adapted from http://www.nesdb.go.th/Main_menu/Macro/Prod_data/table1.4.1.xls, 2003)

While there is a large, diverse literature on the attitudes and objectives of farmers, and the impact of these on farming vocational behaviour (Willock et al., 1999), few studies regarding extension agents' attitudes and behaviour have been conducted. In Thailand, the studies that do exist examine extension agents' opinions towards people's performance (Suthinarakorn, 1986; Pannarai, 1993), or an institution's performance (Duongsasithorn, 1989), and media use in extension (Swanyatiputi, 1988). None of the studies paid attention to personalogical and psychological factors underlying the attitudes of extension agents.

Attitudes and personality traits are "typically conceived of as relatively enduring dispositions that exert a pervasive influence on a broad range of behaviours" (Ajzen, 1987, p. 1). In the domain of social psychology, the concept of attitude has focussed on explanations of consistency of human behaviour. Social psychologists attempt to collect descriptive data regarding attitudes towards various social issues and consider questions of consistency among cognitive (opinion, beliefs), affective (feelings, evaluations), and conative (behavioural intentions) components of attitudes (Ajzen, 1987, 1988; Fishbein and Ajzen, 1975). Similarly, in the domain of personality psychology, the trait concept has focussed attention on explanations of the stable underlying dispositions. Personality psychologists have devoted considerable effort to determine the personality structures in terms of multidimensional trait configuration (Cattell, 1946; Costa and McCrae, 1992b; Eysenck, 1960; 1999). Whatever the behaviour, one or more personality traits appear to underlie or influence the behaviour in question (Ajzen and Fishbein, 1980).

> "Over the past 2 decades, expectancy-value formulations of attitudes have met with considerable success in predicting the influence of attitudes on behavioral intentions and behavior. Two general models – the theory of reasoned action (Ajzen and Fishbein, 1980; Fishbein and Ajzen, 1975) and the theory of planned behavior (Ajzen, 1985) – have been responsible for generating most of the research on attitude-behavior consistency issues."
>
> (Manstead and van der Plight, 1998, p. 1313).

The two models both provide parsimonious explanations of the impact of information and motivation on behaviour. The models imply that people carefully consider available information before they make behavioural decisions, and thus they are considered by some (e.g., Conner and Armitage, 1998) as deliberative processing models.

The TRA assumes that people are normally quite rational, in that they make systematic use of available information, consider the implications of their actions, and thus behave in a sensible manner. Most social behaviour is under volitional control and the theory views an individual's intention to engage, or not, in a particular behaviour as the immediate determinant of the action (Ajzen and Fishbein, 1980). Individuals will have strong intentions to perform a given action if they evaluate it positively, and believe that significant others would like them to perform it. Although the TRA has been successful in predicting and understanding a wide-range of behaviours (Ajzen and Fishbein, 1980), it fails to predict behaviours that are not entirely under an individual's (volitional) control. Thus, the TRA restricts itself to volitional behaviours. Behaviour requiring skills, resources, or opportunities not freely available are not considered to be within the domain of the TRA, or are likely to be poorly predicted by the TRA (Fishbein, 1993).

In an attempt to strengthen the TRA with respect to the behaviours that are not entirely under volitional control, the TPB was developed. It incorporates perceptions of control over performing the behaviour (e.g. knowledge and skills, facilities available, opportunities) as an additional factor in predicting the behaviour. The TPB has become the dominant model in attitude-behaviour literature (Olsen and Zanna, 1993), and it has met with some success (Conner and Armitage, 1998). The model describes the process by which attitude and beliefs determine behaviour, but not the processes whereby other variables (e.g. personality) influence elements of the TPB (Conner and Armitage, 1998).

In the domain of personality psychology, three popular models of personality traits include the 16 Personality Factors (16PF) model of Cattel (1946), the widely accepted three-factor (PEN) model of Eysenck (1960), and the even more widely accepted contemporary five-factor (OCEAN) model of Costa and McCrae (1992b). Although these models disagree about the specific contents and structure of the basic traits needed to describe personality, their general concepts have much in common.

As expert systems are thought of as a new innovation to the agents, it is hypothesised that the agents with an 'open' personality (one of the five factor traits) might have a favourable attitude towards the use of expert systems as their nature is open to new experience. In addition, 'introverted' agents might have a favourable attitude towards the use of expert systems as their nature is reserved. They might feel more comfortable, relative to people contact, with a computer program to obtain information for their decision support work. Although the three models provide an Extraversion (E) scale, only the OCEAN model provides the Openness (O) scale.

Furthermore, relationships between personality and intelligence have gained attention from psychologists (Saklofske and Zeidner, 1995; Sternberg and Ruzgis, 1994). It might be useful if personality and intelligence are studied in parallel to see whether they can make contributions to shared or supplementary variance, when they are used to predict behaviour (Matthews and Deary, 1998).

Two theorists, Gardner and Sternberg, emphasise information processing as an important operation of intelligence and regard intelligence as comprising multiple abilities. Gardner (1983, 1993) stresses the separateness of the various components of intelligence (verbal-linguistic, logical-mathematical, visual-spatial, bodily-kinesthetic, musical-rhythmic, interpersonal, and intrapersonal). Sternberg (1985, 1988), on the other hand, emphasises three thinking abilities (analytical, creative, and practical abilities) and three highly interdependent components of intelligence (metacomponents, performance components, and knowledge-acquisition components) in his Triarchic Theory of Intelligence. The Triarchic Theory of Intelligence is considered very close to the way the agents use these abilities and components in solving farmers' real world problems (see section 4.6 for discussion).

## 1.3 Research Objectives

The objective of this research is to explain extension agents' attitudes towards the use of an example expert system (POSOP) through developing a model that attempts to explain:

(1) how extension agents' attitudes towards POSOP's features, in particular its value as a decision support tool and its user interface, influence their attitudes towards the use of POSOP,

(2) how extension agents' personality traits, in particular the Openness (O) and Extraversion (E) traits, influences their attitudes towards the use of POSOP, and

(3) how extension agents' intelligence influences their attitude towards the use of POSOP.

## 1.4 Research Significance

Primarily, the analysis leads to a basic consideration of how extension agents might develop their method of operations, particularly with respect to expert systems. This deeper understanding potentially leads to developing a more effective extension system. Furthermore, the research results provide preliminary information for policy makers on whether expert systems should be introduced to agricultural extension in Thailand, how they can be introduced, the limitations to the adoption of expert systems, and what resources (e.g., hardware, software) and support (e.g., technical, training) are needed for future adoption. If POSOP is well accepted, it might compensate for scarce experts in rice disease diagnosis in Thailand in the future and save the Ministry of Agriculture and Co-operatives money in training new experts. The next stage in the research would be to follow the use of POSOP over several years and determine whether the model does in reality explain attitudes and use.

In addition, improvements to POSOP, as suggested by the agents, provides not only useful suggestions to meet the needs of the users, but also useful guidelines for the development of future expert systems to enhance their use. Above all, however, the research results move in the direction of embodying people and how they act into providing a clearer understanding of extension agents' modus operandi. This understanding is crucial to the development of improved extension services, and to knowledge itself.

## 1.5 Thesis Organisation

This thesis is organised into 8 chapters. Chapter 1 outlined the background to agricultural extension in Thailand: the development of agricultural extension organisations, the functions and responsibilities of the Department of Agricultural Extension and its structure. Then the research problem, objectives and significance were presented. In Chapter 2 expert systems are introduced, and their development and application in agriculture are discussed. The adoption of innovations and agricultural expert systems are covered in

Chapter 3. The background theories to the research are reviewed and discussed, and then the conceptual framework of the research is drawn in Chapter 4. In Chapter 5 the research design and methods used are presented, and data analyses discussed. The results and discussion are presented in Chapter 6, and finally, the summary and implications are presented in Chapter 7.

# CHAPTER 2

# Expert Systems

## 2.1 Introduction

As the core of this research is about extension agents' attitudes to the use of expert systems, the nature of expert systems, their methodology, development and application, are reviewed in some detail.

An expert system, also known as a knowledge-based system, is a computer-based decision support system. It is regarded as a form of artificial intelligence (AI) (Luger and Stubblefield, 1993; Yazdani, 1986). The concept of expert systems assumes that experts' knowledge can be captured in a computer program and then applied by others when it is needed (McLeod, 1993; Turban, 1993). An expert system attempts to code the heuristic knowledge of human experts. The term heuristics comes from the same Greek root as eureka (to discover) and refers to a rule of thumb, or a rule of good judgment. Heuristics do not guarantee results as rigorously as do some conventional algorithms, but offers results that are good enough most of the time to be useful. The rules allow the system to function as a human expert, advising the user on how to solve a problem (McLeod, 1993). Expert systems are considered by some (e.g., Parsaye and Chignell, 1988) to be the technology for use in the knowledge age, just as early computers were the technology for the information age.

In an attempt to capture human expertise in expert systems, it is important to have clear ideas about human experts (the prototype), that is, what experts and expertise are, what types of knowledge and skills that experts use in problem solving, how they think, process information, and make judgements and decisions. It is also important to understand the structure and properties of expert systems, and the difference between expert systems and conventional computer programs. Most important of all, is understanding how 'expertise' can be captured in a computer program.

In developing an expert system, there are several factors necessary to consider. These include the justification for the system, the knowledge engineering methodologies, the tools available, and the people involved in the system development. In addition, acquiring knowledge from human experts and representing the acquired knowledge in the form that can be used by a computer program, as well as an evaluation of the system, must be taken into account. All these matters are discussed and serve as guidelines for the development of an example expert system (POSOP) for use in this research. Lastly, the application of expert systems in agriculture is discussed. Throughout this discussion reference is made to the methods used in developing POSOP and examples provided. Thus this chapter serves both to review expert system development, and to describe POSOP (see Appendix G for further details of POSOP).

## 2.2 The Definitions of an Expert, Expertise, and an Expert System.

"All experts in a given field are alike, but each in his or her own way." (Regoczei, 1992, p. 309). Experts can 'automatically' do things that non-experts can only do with great effort, or not at all. In other words, what comes easily to an expert comes only with difficulty, or does not eventuate at all, to the novice (Sternberg and Frensch, 1992).

> "An expert is a person who, because of training and experience, is able to do things the rest of us cannot; experts are not only proficient but also smooth and efficient in the action they take. Experts know a great many things and have tricks and caveats for applying what they know to problems and tasks; they are also good at plowing through irrelevant information in order to get at basic issues, and they are good at recognising problems they face as instances of types with which they are familiar. Underlying the behaviour of experts is the body of operative knowledge we have termed expertise."
>
> (Johnson, 1983; cited in Parsaye and Chignell, 1988, p. 328).

Expertise is difficult to extract in a tangible form from a human expert (Broner, King and Nevo, 1990). Bolger (1995) defines expertise in terms of 'competence' and proposes that it is necessary to consider performance as a reflection of an underlying competence. Social definitions of expertise such as professional qualifications, salary, position within an organisation, number of publications, media profile, number of years on the job and so forth may not be correlated particularly well with actual ability (Bolger, 1995; Cooke, 1992). Turban (1993) emphasises that expertise is domain specific and defines expertise as “the extensive, task-specific knowledge acquired from training, reading, and experience.” (Turban, 1993, p. 469).

Definitions of expert systems have been given by many from different points of view. For example, from an expertise model (Feigenbaum, 1988; cited in Doluschitz and Schmisseur, 1988), from a functional model (Parsaye and Chignell, 1988), and from an expertise transfer point of view (Turban, 1993). As this study looks at transferring expertise from expert (s) to a computer, and then to non-experts to improve decision-making, Turban’s definition is presented:

> “An expert system is a system that employs human knowledge captured in a computer to solve problems that ordinarily require human expertise. Well-designed systems imitate the reasoning process experts use to solve specific problems. Such systems can be used by non-experts to improve their problem solving capabilities.”
> (Turban, 1993, p. 466).

Two key questions arise from this definition: what types of knowledge and skills experts possess and use in problem solving, and how can this knowledge and skills be captured and represented in an expert system computer program?

There are numerous distinctions between types of knowledge (Regoczei and Hirst, 1992). However, there is one distinction that is useful in developing expert systems – ‘knowledge that’ and ‘knowledge how’ (Gordon, 1992). This distinction is enshrined in computer science between data structures and algorithms (Regoczei and Hirst, 1992).

According to Gordon (1992), knowledge that is termed ‘declarative knowledge’ consists of what is known about objects, events, static relationships between concepts and so forth. It is commonly assumed that declarative knowledge is represented in a propositional network form, is relatively static, and is easy to verbalise.

Knowledge on how to do something is termed ‘procedural knowledge,’ and is knowledge about how to perform various cognitive activities, or the dynamic process of operating on knowledge. Because of the dynamic nature of procedural knowledge, it is often represented by IF-THEN production rules. Although declarative knowledge is often described as knowledge 'that', and procedural knowledge as knowledge 'how', declarative knowledge can include knowledge about procedures. For example, fixing a flat tire needs the proper steps to follow. This type of knowledge is a special type of declarative knowledge consisting of an ordered sequence of actions.

Possessing both declarative knowledge and procedural knowledge may be insufficient to solve problems at an expert level. Bolger (1995) comments that other problem solving skills, such as problem recognition, interpretation and information gathering are important skills as are declarative and procedural domain knowledge. A knowledge of one's limitations and abilities is also important.

Turban (1993) lists examples of the types of knowledge held by experts. These include: facts and theories about the problem area, hard-and-fast rules and procedures concerning the problem area, rules (heuristics) concerning problem solving in a given problem situation, global strategies for problem solving, and meta-knowledge (knowledge about knowledge). These types of knowledge enable experts to make better and faster decisions than non-experts in solving complex problems.

Gordon (1992, pp. 100-101) reviews a three-stage model of skill acquisition necessary to becoming an expert and summarises the stages as follows.

'Cognitive stage.' In the beginning, declarative knowledge from various sources is accumulated. If a task must be performed, relevant information of the declarative knowledge is retrieved from a person's long-term memory and operated on by domain-general procedural knowledge (procedures that can be applied to declarative structures in any context). In this stage, poor quality of decision-making and problem solving can be assumed, that is, it tends to be slow, tedious, and prone to error.

As a person becomes more 'competent' in the domain, he/she gradually moves into a second, 'associative stage.' The repeated practice of applying declarative knowledge in given situations results in domain-specific procedures, that is, when specific conditions are directly associated with the resultant action, the need for operating on declarative knowledge gradually becomes bypassed. The advantage to this process is that when the environment conditions and the procedural rule match, the action is automatically invoked, circumventing the longer and more tedious process of retrieving declarative knowledge and applying the general procedure to it.

Finally, there is the 'autonomous stage' in which the procedures become highly automated. That is, the associations between specific conditions and the resultant actions become strengthened and more highly specialised or tuned towards particular types of situations. At this stage, procedural knowledge operates in a very fast automatic fashion. Simple productions become composed into, or replaced by, more complex, inclusive productions. As the latter type of productions compress a large number of instantaneous conditions and resulting actions, a person's ability to verbalise knowledge skill decreases. When performance of a task has become completely automated, cognitive resource is no longer required. Processing is autonomous and unavailable to conscious awareness.

The model suggests that as a person becomes competent in a given domain, he/she shifts away from using symbolic or declarative knowledge towards relying on perceptual, non-verbalisable procedural knowledge. Expertise is acquired through the initial use of declarative knowledge and is then later compiled into procedural knowledge (Gordon, 1992). This model may explain why knowledge acquisition is a critical stage that frequently impedes expert system development. It requires years (usually several) to become an expert, and novices become experts only gradually (Turban, 1993).

Turban (1993) believes expertise is usually associated with quantity of knowledge and a high degree of intelligence, but it is not always connected to the 'smartest person,' experts' knowledge is well stored, organised, and quickly retrievable. Experts learn from past successes and mistakes. In addition, experts can excellently call up patterns from their experience; and, typically, human expertise includes behaviour that involves recognising and formulating a problem, solving the problem quickly and properly, explaining the solution, learning from experience, restructuring knowledge, breaking rules, determining relevance, and an awareness of limitations.

Experts can deal with a problem arbitrarily (perhaps because of mental subjective probability) and convert it to a form that results in a rapid and effective solution. Problem-solving ability is necessary, but it is not sufficient by itself. Experts should be able to explain the results (but sometimes cannot because of automaticity of expertise), keep up with new knowledge about the domain, restructure knowledge and break the rules wherever there is a need (i.e., know the exception to the rules) and determine whether their expertise can be applied. All these activities must be done efficiently (quickly and at low cost) and effectively (with high quality results). Finally, experts 'degrade gracefully,' meaning that as the problem lies close to or beyond the boundaries of their expertise, they gradually become less proficient at solving problems (Turban, 1993).

## 2.3 How Experts Think, Process Information, Make Judgements and Decisions

In building an expert system, the most important characteristics in mimicking a human expert are the thinking, reasoning, judgement and decision-making processes of the experts.

Cognitive research in expertise has investigated expert-novice differences in virtually every aspect of cognitive functioning, from memory and learning to problem solving and reasoning. Two interesting findings are (Shanteau, 1990):

(1) Expertise is domain specific. Any special skills an expert possesses are quickly lost outside her/his boundary of expertise. It appears that crucial aspects of an expert's cognitive process are tailored to the unique characteristics of a particular problem area. For instance, novices have been found to use backward reasoning from the unknowns to the givens. In contrast, experts use forward reasoning from the givens to the goal using stored 'functional units' (Larkin, 1979). This forward reasoning ability only develops in specific domains. Thus, the information processing of experts becomes 'domain adapted' (Slatter, 1987).

(2) The information processing of experts relies more on automated processes than on controlled processes (Shiffrin and Schneider, 1977). Automated processes are comparable to visual perception or pattern recognition and often parallel and function independently. Controlled processes, on the other hand, are comparable to

deductive reasoning and more linear and sequential. Controlled processes underlie the development of automated processes. With consistent training, some controlled processes may become automated over time (Larkin et al., 1980). With experience, experts come to rely less on deductive thinking and more on pattern recognition based thinking.

An approach to characterising expert judgement has been to look at the amount of information used in making decisions. Presumably, experts should make use of all relevant information, but Shanteau (1992) concluded from a review of literature that experts often use a smaller number of significant cues relative to novices. However, the information used is more relevant. Therefore, the amount of information used does not in fact reflect the degree of expertise, but the type of information used does. Both experts and novices appear to know how to recognise and make use of multiple sources of information, but novices lack the experience or ability to separate relevant from irrelevant information sources. An interesting question is how this experience is translated into the ability to distinguish relevant from the irrelevant. One possibility in an organisational setting is that experience leads experts to develop a 'strategic conceptualisation' of how to make rational decisions (Neale and Narthcraft, 1981; cited in Shanteau,1992). Another is that the interactive training appears to reduce the influence of irrelevant information in experienced decision makers (Gaeth and Shanteau, 1984).

Expert-novice differences have been studied in a wide range of domains, ranging from playing chess to fixing cars (Sternberg, 1988). A consistent finding is that experts have better perceptual skills (Larkin et al., 1980) and more complex representations of information than do novices (Sternberg, 1988). For example, a chess master can accurately recall 90% of the position on a chess board while a chess novice can recall only 20-25% (Larkin et al., 1980).

Another difference between the experts and the novices is that experts can chunk information about a given domain superior to novices. Chunking of information refers to putting pieces of information together into a single, unified, and coherent representation. For example, what might seem to be five unrelated facts about how a car works may seem to a mechanical expert to be just one network of interrelated items. This difference applies not only to novices-experts, but to younger-older children, and to children-adults (Sternberg, 1988).

In summary, experts, within their domains, are knowledgeable, competent, skilled, and think in qualitatively different ways from novices. They are able to screen the relevant from the irrelevant information sources. This information provides a sufficient basis for capturing an expert's knowledge, thinking and reasoning processes for developing an expert system. To function like experts, the system should be task-specific and cover a narrowly defined domain.

## 2.4 Analogy between Human Experts and Expert Systems

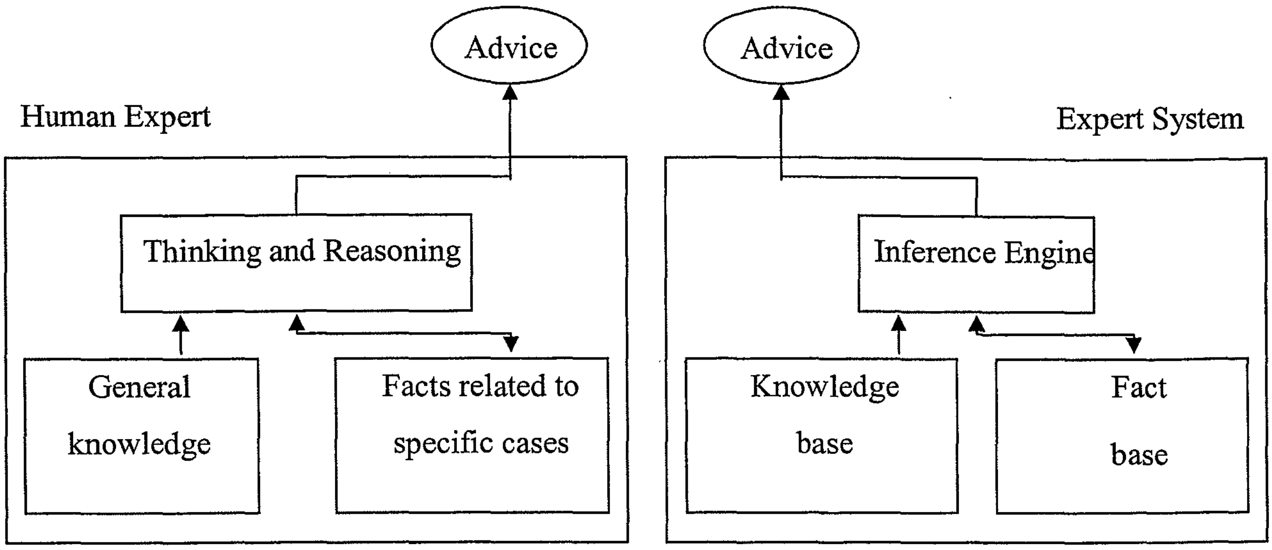
A human expert uses knowledge and reasoning to draw conclusions. As with a human expert, an expert system relies on a knowledge base and performs reasoning by mimicking human experts in associating pieces of knowledge. Thus the structure, or architecture, of an expert system partially resembles how a human expert is thought to perform. Parsaye and Chignell (1988) draw an analogy between an expert and expert system, as shown in Figure 2.1.

The first part of human expertise is a long-term memory of facts, structures, and rules that represent expert knowledge about the domains of expertise. This is analogous to the 'knowledge base' in an expert system. The second part of human expertise is a method of reasoning that can use an experts' knowledge to solve problems. It is where the reasoning function is carried out in an expert system and is analogous to the 'inference engine'.

In this analogy the inference engine mimics thinking, while knowledge is contained in the knowledge base. The knowledge contained in an expert system includes general problem solving knowledge as well as specific domain knowledge.

The difference between the knowledge base and the inference engine is comparable with the distinction between general-purpose reasoning and domain specific knowledge. In general, the domain knowledge is stored in the knowledge base while the general problem solving knowledge is mostly built into the way the inference engine operates. Thus the same inference engine can be used to reason with different knowledge bases.

**Figure 2.1** An analogy between human experts and expert systems



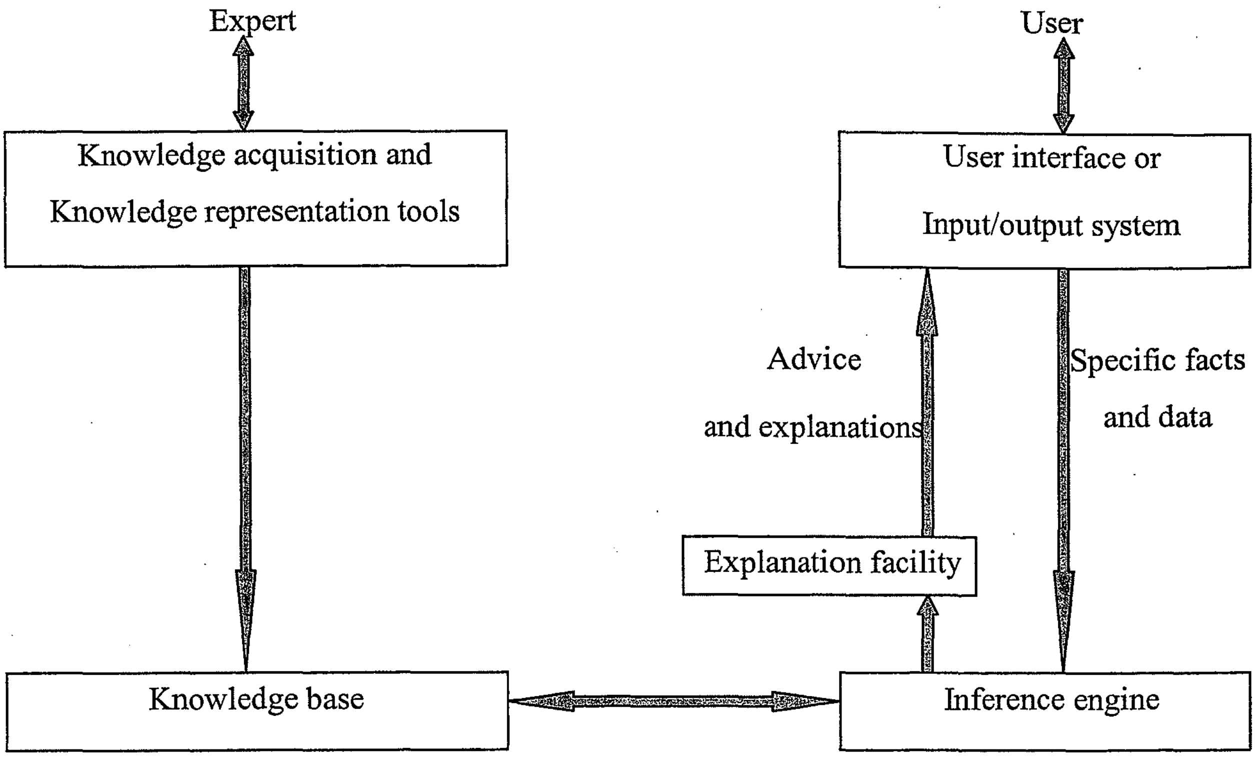

**Source:** Parsaye and Chignell (1988), p. 32

## 2.5 The Structure and Properties of Expert Systems

Although there is no general standard for the structure or architecture of expert systems, most include at least four components: a knowledge base, an inference engine, a user interface, and an explanation facility (Doluschitz and Schmisseur, 1988; Forsyth, 1986; Luger and Stubblefield, 1993; McLeod, 1993; Parsaye and Chignell, 1988; Rolston, 1988; Turban, 1993) as illustrated in Figure 2.2

Both domain facts and heuristics are stored in the knowledge base. Facts of the domain are pieces of information widely shared and generally publicly available within the domain. Heuristics, on the other hand, are mostly privately and individually held. Heuristics refers to rules-of-thumb, rules of good judgements, and sometimes experience-based-guesses that typically characterise human expert-level decision-making. In order for an expert system to solve a problem, a program must have both facts and heuristic knowledge in its knowledge base. The knowledge base is usually developed with the assistance from at least one human domain expert (Doluschitz and Schmisseur, 1988).

**Figure 2.2** Structure of an expert system




**Source:** Adapted from Doluschitz and Schmisseur (1988), p. 174.

Apart from a knowledge base, an inference system or procedure, also commonly called an inference engine, is included in an expert system. This system holds the general problem-solving approach. It decides which heuristics are applied to the problem, accesses the appropriate rules in the knowledge base, executes the rule, and determines which solution is acceptable when the rules are fired up. In effect, an expert system is run by the inference engine (Doluschitz and Schmisseur, 1988).

Besides the knowledge base and inference engine, at least two important expert system building tools, commonly known as knowledge acquisition and knowledge representation, are included in the expert system environment. When building the expert system, the knowledge engineer uses these tools to acquire, encode, and debug knowledge within the knowledge base (Doluschitz and Schmisseur, 1988).

Just as a human expert communicates with a client, an expert system must have a component that facilitates bidirectional communication between the system and the user. This component is known as the input/output system, also commonly called the user interface. Through it, users supply information, which describes the problem, and receive requests for additional information about the problem as well as the reasons behind its advice or recommendations (Doluschitz and Schmisseur, 1988).

The user interface is an essential part of an expert system and equally as important to other components in the success of the system (Broner, Parente and Thomson, 1992; Hockman, Pearson and Litchfield, 1994; Nuthall and Bishop-Hurley, 1996a; Wolak and Carton, 1992). It handles all the communication between the user and the expert system. The user's impression of the expert system usually depends a great deal on the nature of the interface. The way that information is presented to the user should conform to the user's model of the task and expectations. It is generally referred to as 'cognitive compatibility'. Compatibility exists when the system conforms to the concepts that are familiar to the user, and the information is presented in a non-confusing and understandable way (Parsaye and Chignell, 1998).

Wolak and Carton (1992) noted that clients seek out human specialists with good communication and interpersonal skills. Consequently, it is likely an expert system must have a user interface which exhibits good communication techniques. If the user interface is tedious to use, the potential user will likely never use the system on a continuing basis. They proposed that the concept of 'client-specialist' communication must be addressed in expert system development. Long question sessions without providing feedback should be avoided. Users have reacted favourably where intermediate answers are displayed after groups of two or three questions. From Wolak and Carton's observations, users generally exhibited boredom or frustration during an extremely long question session. Both reactions may lead to non-use of the system, or an incomplete analysis of the problem. Similarly, Adoum (1992) reported that users who tried the system, and then stopped, gave the reason for stopping as the burdensome data input requirements.

Just as human experts explain their recommendations or decisions, expert systems need to justify and explain their actions. The part of an expert system that provides explanations is commonly called an explanation facility. The explanation facility serves both a social need and a technical purpose. It not only helps the end-user feel more assured about the actions of the expert system, but also helps the developer follow through the operation of the expert system (Parsaye and Chignell, 1988).

Also, good explanations (i.e., relevant, convincing, and understandable) increase user understanding and acceptance of the systems (Greer et al., 1994). Likewise, Nuthall and Bishop-Hurley (1996b) noted that the farmer would like the expert system conclusions to be extensive and reasoned rather than simple 'do this' and 'do that' statements. They wanted a conditional set of suggestions like, for example, "you should follow a course of action involving x, y, and z, but if temperature should increase above 15° in the next day or so you should contemplate action a, b, c, etc." (Nuthall and Bishop-Hurley, 1996b, pp. 38-39). This is, of course, in addition to a full explanation why the particular conclusions had been reached.

## 2.6 The Difference between Expert Systems and Conventional Computer Programmes

Expert systems, although markedly different, should be considered as extensions to conventional computer programs, not as competitors. The difference is that expert systems deal with a knowledge base (symbolic processing) while conventional programmes deal with data base (data processing). That is, users are required to draw their own conclusions from facts retrieved and/or calculated by the conventional programs. In contrast, expert systems, consisting of both declarative and procedural knowledge, use reasoning to draw conclusions from stored facts (Doluschitz and Schmisseur, 1988).

Expert systems are also typically reserved for problems where algorithmic solutions do not exist. Therefore, heuristic searching is required to reduce the search effort. This is in sharp contrast to conventional computer programs. However, because of these heuristics, often sub-optimal solutions are produced (Doluschitz and Schmisseur, 1988; Parsaye and

Chignell, 1988). Also, expert systems usually do not solve sets of equations or perform other extensive mathematical computations. These are effectively manipulated by conventional algorithmic programs. Instead, symbols representing problem concepts can be created and manipulated. This unique feature provides expert systems with the ability to take a problem stated in some arbitrary initial form and convert it to a form appropriate for processing by expert rules. This reformulation capability can range from simple processes to a complete re-conceptualisation of a problem (Doluschitz and Schmisseur, 1988).

Another distinction between expert systems and conventional programs is that in expert systems the control structure is separate from the domain knowledge area. Thus, modifying, updating and enlarging the expert program can be more easily achieved. In conventional programs, modifications are generally more difficult because changes in one part of the program may affect other parts of the program. Thus, it is necessary to carefully examine for the impacts (Doluschitz and Schmisseur, 1988). This is true in simple problem domains (i.e. disease, weed/pest diagnosis and control) but if the nature of the problem changes then the inference structure might also change.

## 2.7 Expert System Development

Human expertise is well recognised and even vital in many situations. It is scarce and expensive. It takes years to learn the necessary skills to become an expert. Human experts become sick, retire, and die without leaving their expertise behind. Thus, there are convincing reasons for backing up, or even replacing it with artificial expertise in the form of an expert system. Once the costs associated with building an expert system have been absorbed, the system can be copied onto magnetic media in seconds or minutes, and may be used again and again with minimal charge. (Forsyth, 1986; Parsaye and Chignell, 1988). But it does need constant updating as conditions and knowledge change.

Like any other software development effort, developing an expert system requires some discipline in the methods and processes that are used. Enforcing discipline can be difficult as a result of 'social issues' that interfere with developing expert system teams. These issues are often different from the issues involved in conventional software development, since the new technologies of expert systems have arrived well before any understanding about how it can be integrated into a larger social context (Parsaye and Chignell, 1988). Their primary role as a decision support tool has long been known; however, their other potential roles, such as an extension tool (Gum and Blank, 1990; Plant and Stone, 1991; Rafea, 1998), a training tool (Fidanza and Waddington, 1990; Nash et al., 1992; Rafea and Shaalan, 1996, Stewart, 1992; http://www.sbaer.uca.edu/Research /1999/WDSI/ 99wds650.htm, 2004), an educational tool (Broner, Parente and Thompson, 1992; Fidanza and Waddington, 1990; Pasqual, 1994), and a human expert assistant (Hart, 1986; Ganeshan and Chacko, 1990) have been stressed. Their roles in Thai agricultural extension services remain to be defined.

Expert systems derive their power from their knowledge, so the heart of any expert system is the knowledge it contains, and it is the effective use of this knowledge that make its reasoning successful. It is difficult to define knowledge in the abstract and use the knowledge to support the system reasoning process (Luger and Stubblefield, 1993; Parsaye and Chignell, 1988; Rolston, 1988). The declarative and procedural knowledge of human experts must be brought out in the open and represented in a form that can be used for reasoning by an expert system through a process referred to as 'knowledge acquisition and knowledge representation' (Forsyth, 1986; Luger and Stubblefiled, 1993; McLeod, 1993; Parsaye and Chignell, 1988; Turban, 1993).

Apart from knowledge acquisition and knowledge representation, there are several factors necessary to consider before developing a successful and useful expert system. These include the justification for its development, the knowledge engineering methodology, the tools available, and the people involved in the system development, as well as, the evaluation of the system must all be taken into account.

### 2.7.1 Justification of an Expert System Development

Parsaye and Chignell (1988 p. 293) suggest that before developing any expert system, there are questions to be considered:

(1) Why this expert system is being developed?
(2) Will the effort in developing the system be justified?

(3) What will the return on investment be?

(4) How will the expert system be built?

(5) Who is going to make contributions to the system development?

(6) What tools are available?

(7) Can the system be built in the way that it is envisaged?

(8) What can go wrong?

(9) When to stop developing?

(10) How the system is maintained after it has been built?

The first three questions are the same as for any software development effort. According to Turban (1993, p. 636) of the following eight factors, at least one should be present to justify an expert system:

(1) The solution to the problem has a high payoff.

(2) The expert system can preserve scarce human expertise so that it will not be lost.

(3) Expertise is needed in many locations.

(4) Expertise is needed in hostile or hazardous environments.

(5) The expertise improves performance and/or quality.

(6) The system can be used for training.

(7) The expert system solution can be derived faster than a human's solution.

(8) The expert system is more consistent and/or accurate than humans.

The derived benefits in one or more of these areas must be compared against the costs of developing the system (Turban, 1993).

If the expert system can be justified and will provide a positive return on investment, the minimum requirements for development include, a knowledge engineering methodology, the availability of expert system building tools, and the cooperation of people involved in the system development.

### 2.7.2 Knowledge Engineering Methodologies

The knowledge used by the expert system is captured and encoded by a person called a 'knowledge engineer' who interviews the expert, extracts the knowledge, and builds the expert system. The methodologies used for dealing with experts in this manner have become known as 'knowledge engineering' techniques (Parsaye and Chignell, 1988). Perhaps the major difficulty of expert system technology is that there is no commonly accepted methodology. Each knowledge engineer works, at best, with a different methodology and, at worst, with none, being guided exclusively by her/his experience and/or intuition. However, one expert system development methodology after another appeared during the 1980s in an attempt to standardise and simplify expert system construction (Recio, Acuna and Juristo, 1999).

Recio, Acuna and Juristo (1999) reviewed and summarised knowledge engineering methodologies (Weiss and Kulikowski, 1984; Waterman, 1986; Wolfgram et al., 1987; Pasaye and Chignell, 1988; Bowman and Glover, 1988; Wielinga et al., 1989; Alberico and Micco, 1990; Edwards, 1991; Go'mez et al., 1997). These methodologies typically include, or are based on, a conceptual framework that establishes the necessary support for the different phases of expert system construction. With respect to the different methodologies, the generic expert system phases explicitly, or implicitly, present in the expert systems prototyping process are as follows (Recio, Acuna and Juristo, 1999, pp. 21-22):

(1) **Feasibility study** – before an expert system is built, the task thought to be performed by the system must be evaluated from the viewpoint of knowledge engineering. Several questions need to be answered: Can the task be addressed using expert system technology?, Is a traditional software system sufficient?, Would it suffice to buy a software package?, or Can the task be performed by a computer?

(2) **Knowledge acquisition** – as the problems addressed by expert systems are often ill-structured, and user requirements are seldom clearly defined , the most complex and longest activity in expert system construction is to acquired the information and knowledge needed to understand the domain, the problem and the problem solving process. This phase produces a set of unorganised information and knowledge.

(3) **Conceptualisation** –to understand the domain, the knowledge acquired is modelled conceptually by constructing a preliminary mental or conceptual framework. Work during this phase, the preliminary framework, is made explicit. Once the problem, its environment, and the solution are clearly understood, knowledge is said to have been conceptualised. This means that if anyone 'walks through' the conceptual model, he/she would be able to solve the problem in the same manner as the expert.

(4) **Knowledge formalisation or knowledge representation** – the work of knowledge engineers should focus on the real world and its understanding. Once the domain has been conceptualised, a formal language to represent the knowledge conceptualised in the preceding phase is selected.

(5) **Implementation** – the formal model obtained must be translated into a computer-readable language. Where a knowledge engineering environment is used, this phase can be completely automated.

(6) **Evaluation** – all the outputs from the above phases must be verified and validated to ensure that the conceptual, formal, and computer models are correct, valid, usable and useful.

Ricio, Acuna and Juristo (1999) have developed a methodology for designing and constructing an expert system called IDEAL (Table 2.1). This methodology was recently updated and developed for both software engineering and knowledge engineering. It constitutes a complete guide for the knowledge engineer as the methodology specifies both what to do (declarative) and how to do it (procedural) in order to produce and maintain an automatic solution to a real world problem. Each phase includes a set of detailed complementary techniques, indicating when they are to be used. The details of phases and stages of IDEAL methodology can be found in Recio, Acuna and Juristo (1999).

**Table 2.1** The IDEAL methodology: Phases and Stages

| Phase | I<br>Task identification | II<br>Development of demonstrator and other prototypes. | III<br>Final system construction and execution | IV<br>Proper technology transfer (TT) | V<br>System maintenance |
|---|---|---|---|---|---|
| Stage 1 | Definition of task characteristics, knowledge acquisition. | Solution conception: Decomposition into subproblems and/or like problems. | Requirements and design of integration with other systems (inferencing with other hardware and software systems). | Organisation of TT | Definition of general system maintenance. |
| Stage 2 | Feasibility study | Knowledge acquisition and conceptualisation. | Integration, implementation and evaluation of full system. | Documentation of system built | Definition of knowledge base maintenance. |
| Stage 3 | Application requirements | Knowledge formalisation; computer architecture definition. | Acceptance by customer | Evaluation of transfer and documentation. | Acquisition and conceptualisation of new knowledge. |
| Stage 4 | | Tools selection and implementation. | | | Evaluation of new knowledge. |
| Stage 5 | | Prototype validation and evaluation. | | | |
| Stage 6 | | Definition, development and validation of new requirements, and design; repeat stage 2-6 for each prototype. | | | |

**Source:** Recio, Acuna and Juristo, (1999), p. 23

The results obtained from following the IDEAL methodology (Recio, Acuna and Juristo, 1999) have been very satisfactory for two basic reasons: (1) the phases of the methodology are well suited to the phases in which the work must be performed, and serve at all times as a reference point, and (2) the documentation obtained facilitates problem understanding and implementation for future changes, extension or new system development both by the people who participated in the system development, and people joining the team in the future. The only limitation was the feasibility test as some questions are oriented to other sectors. The IDEAL methodology provided the guidelines for constructing the example expert system (POSOP) used in this research.

### 2.7.3 Tools Available for Building an Expert System and People Involved.

The way in which an expert system should be built is strongly affected by what tools are available. As with any other building process, the construction of an expert system can be made considerably easier and cost-effective given effective tools. A large number of tools already exist, either in research laboratories, or as commercial shell software (Alty, 1989). Some selected tools are discussed in Bielawski and Lewand (1988) and Waterman (1986).

Selecting expert system building tools can be problematic as some shells have non-standard components, or no interface with other software such as databases or spreadsheets. Some do not support graphic user interfaces that enhance a user's understanding ('a picture is worth a thousand words.'). Rothenberg (1989) provided a list of examples of tool capabilities and supporting features that can be used as criteria for selecting the shell (Table 2.2).

In this research, the shell software selected had to support the Thai language. Furthermore, the expert system had to be compatible with the current hardware and software in use by the extension agents (Appendix D, Table D2-D3).

The primary people involved in developing an expert system are the domain expert, the knowledge engineer, and the end user. The development of an agricultural expert system requires the combined efforts of experts from many fields of agriculture and can only be accomplished with the cooperation of the experts, who provide their knowledge, the cooperation of competent knowledge engineers, who extract and encode experts' knowledge into an expert system, and the involvement of the extension agents and farmers, who will use the system.

**Table 2.2** Examples of tool capabilities and supporting features.

| Capability | Supporting Features |
|---|---|
| Arithmetic processing | Arithmetic operators, extended floating point |
| Certainty handling | Certainty factors, fuzzy logic |
| Concurrency | Distributed processing, parallel processing |
| Consistency checking | Knowledge base syntax checking |
| Documenting development | Assumption/rationale history, code/data annotation |
| Explanation | Execution trace, knowledge base browsing |
| Inference & control | Iteration, forward/backward chaining, inheritance |
| Integration | Calling other languages, interprocess calls |
| Internal access | Tool parameter setting functions, source code |
| Knowledge acquisition | Rule induction, model building aids |
| Knowledge-base editing | Structure editors, graphic rule lattice |
| Life cycle | Tool support for target system life cycle support |
| Meta-knowledge | Rules controlling interface, self organising data |
| Optimisation | Intelligent look-ahead, caching, rule compilation |
| Presentation (I/O) | Text, graphics, windows, forms, mouse |
| Representation | Rules, frames, procedures, objects, simulation |

**Source**: Rothenberg (1989), p. 217.

### 2.7.3.1 Expert Cooperation

Turban (1993) notes that the developers of the many expert systems that are now functioning had little trouble in gaining the cooperation from experts as their experts were researchers, professors, or maintenance experts due to retire soon. They tended to cooperate as the whole idea of expert systems was challenging, new, and innovative. This cooperative situation may change when different types of experts are involved. Experts are sceptical and think, 'what's in it for me?', 'why should I contribute my wisdom and risk my job?'.

For these reasons, before developing an expert system that requires the cooperation of experts, the following questions should be considered:

(1) What should experts be compensated for their contribution (e.g., in the form of royalties, a special reward, or payment)? Each expert values each form differently.
(2) Who can tell whether the experts are telling the truth about the way they solve problems? Knowledge is power; thus why should experts give away their power?
(3) How can experts be sure that they will not lose their jobs, or that their jobs will not be de-emphasised, once the expert system is put into full operation?
(4) Are the experts concerned about themselves and the other people in the organisation? The introduction of an expert system may risk the experts' job as well as the other people's job, and what can be done in such cases?

In general, some incentive should be used to influence experts so that they will cooperate fully with the knowledge engineer. Furthermore, it should be noted that 'expertise' is always changing so experts are required to keep a system current.

Lightfoot (1999) notes that the development of expert systems generally assumes that experts willingly give up their knowledge. This is unrealistic and maybe a reason why some expert system projects fail. Lightfoot (1999) classifies unwilling experts into 3 types: unintentional misrepresentation, intentional misrepresentation, and uncooperative. Each type is classified into 2 characteristics: local and cosmopolitan. He also provides 6 strategies to motivate a specific type of unwilling expert. These strategies will help knowledge engineers convert more unwilling experts into cooperative experts.

#### 2.7.3.2 Knowledge Engineer Competence and Availability

In developing an agricultural expert system, it may be appropriate for the experts to meet and discuss the optimal methods, for example, to plant and care for certain crops. They provide information about the soil types, weather conditions, and water supplies essential for productive crops. Details regarding cutting, soil preparation, types of irrigation systems, pest control, fertilisation, disease treatment, and harvesting are collected and catalogued.

The knowledge engineers not only elicit, but also structure, the experts' knowledge through interview and the analysis of existing documents. They figure out the reasoning process by which the experts make decision based on their knowledge in the form of facts and rules. The knowledge engineers then code this knowledge into a shell. In this role, the knowledge engineers act as a go-between the experts and the computer to help experts structure the domain knowledge. Once an expert system prototype is developed, it is commented on and validated by the experts. The prototype is revised as necessary (http://potato.claes.sci.eg/claes/bes.htm, 1999).

A good knowledge engineer requires good communication skills, intelligence, tact and diplomacy, empathy and patience, persistence, logicality, versatility and innovativeness, self-confidence, domain knowledge, and programming knowledge. It is unlikely that a knowledge engineer would have all these qualities, since personnel for a particular project are often sought from existing staff, instead of employing new specialists. However, the selection of the knowledge engineer will have a crucial effect on the success of expert system development (Hart, 1986). Particularly in agricultural and resource management organisations, there is often a shortage of such knowledge engineers and of the funds necessary to employ them. This may cause a bottleneck in agricultural expert system development (Plant and Stone, 1991), especially if a cost-benefit ratio from developing an expert system is taken into account

#### 2.7.3.3 User Involvement

It is generally accepted that users should be actively involved in the development process of expert systems (Berry and Broadbent, 1987) and be an integral part of expert systems evaluation (Liebowitz, 1986; Hochman, Pearson and Litchfield, 1994). User involvement in the development of software leads to the desired effect of 'ownership.' An expert system developed for extension agents without their involvement is likely to be rejected. Reasons for user rejections include: it may not meet the users' needs, it may not suit the users' workplace, it may use language with which users are not comfortable, and it may give recommendations or explanations that users are not prepared to accept (Hochman, Pearson and Litchfiled, 1994). In addition, the system may be beyond the users' capabilities as being a computerised decision support system, it requires basic computer knowledge and skills. This may put some intellectual demands on users.

Involvement of users in system development can be achieved by identifying user needs and attitudes, modifying the system after observing users' reactions to the system at various stages of the development cycle, evaluating both the usability of the system in the workplace and acceptability of recommendations given by the system, and getting the user directly involved in the development of the knowledge base (Hochman, Pearson and Litchfiled, 1994).

Joint efforts have an advantage in that more knowledgeable people are available to potentially support it after it is built (Parsaye and Chignell, 1988). On the other hand, where too many people are involved, disagreement may be difficult to logically resolve.

Even with expert cooperation, a competent knowledge engineer, and user involvement, an expert system development project can still fail for a number of reasons. These include (Parsaye and Chignell, 1988, pp. 294-295):

(1) Underestimation of the knowledge required and the difficulty in acquiring it, or the expert has difficulty in expressing how the knowledge is structured.
(2) Departure of key members of the development team without leaving behind sufficient documentation of their activity. The system never fully recovers from the resulting internal chaos.
(3) Insufficiency of financial support, or changes in internal policy or management, the level of resources originally promised is not fulfilled.
(4) Slowness of the inference engine when the system is fielded may produce unacceptably poor real-time performance. This problem can be remedied with a more powerful computer and advanced shells.
(5) The system cannot be used due to either a poor interface design or the lack of clear instructions.
(6) Unavailability of staff to keep the system updated and maintained as the knowledge in the domain changes. Consequently, the system falls behind the knowledge domain.

A final question can often be overlooked, – 'when to stop developing?' An expert system can always be refined although additional knowledge may mean that a system has to be restructured. Deciding when development stops and the system becomes operational can be a difficult decision. A serious attempt should be made at the beginning of the development process to think through the stages of developing the expert system and anticipate any flaws or pitfalls that may be encountered (Parsaye and Chignell, 1988). In this research, this question is critical, as stopping too early may result in an immature system that is likely to be rejected by extension agents, while stopping too late may mean the study not being able to be completed within the time frame.

### 2.7.4 Knowledge Acquisition

The process of seeking out the knowledge required by an expert system is referred to as 'knowledge acquisition.' The goal of knowledge acquisition is to model the knowledge of one or more experts in a way that will allow it to be encoded into an expert system. The ratio of effort expended to results achieved for the expert system as a whole is often decided by the knowledge acquisition process (Parsaye and Chignell, 1988; Recio, Acuna and Juristo, 1999). The process includes eliciting knowledge from different sources such as domain experts, textbooks, maps, and real world observations, and also analysing, interpreting, structuring, and recording knowledge then transforming this knowledge into a suitable machine representation (Kidd, 1987; Enting, et al, 1999).

Acquiring knowledge from experts is a complex task that frequently creates a bottleneck in expert system development (Spangler, Ray and Hamaker, 1989; Plant and Stone, 1991; Rafea et al., 1993; Turban, 1993). This remains true (Enting et al., 1999; Heald et al., 1995). The knowledge acquisition process is critical as human experts seldom analyse the contents of their thoughts. Their expertise is acquired through years of experience and is stored in ways of which they are entirely unaware (Broner, King and Nevo, 1990) As a result, the intermediate steps in their reasoning seem obvious to them and they cannot provide an overall account of how their decisions are made at a level of detail required by a machine reasoning process (Parsaye and Chignell, 1988).

Each knowledge acquisition approach developed in the late 1970s and early 1980s has been a variation of 'talking to the expert.' The questioning that occurs during interviewing is a simple way to elicit knowledge, but there is little in the way of methodology to guide the interaction between the expert and knowledge engineer (Parsaye and Chignell, 1988).
A number of approaches to knowledge acquisition have been suggested (Hart, 1986; Kidd, 1987). The three basic approaches are:

**2.7.4.1 Interview** – the most common approach to knowledge acquisition. In this approach a knowledge engineer elicits knowledge from the human expert through a series of interviews and encodes it in the expert system. This approach is time consuming of both the expert (s) and the knowledge engineer (s) (Michalski and Chilausky, 1980) and is highly independent on the knowledge engineer's skills and expensive (Parsaye and Chignell, 1988). For example, Boyd and Sun (1994) involved two knowledge engineers and five domain experts in the knowledge acquisition process in prototyping an expert system for diagnosis of potato diseases.

**2.7.4.2 Induction** – in this approach a computer extracts knowledge by examining data and examples and then generalises them to obtain the required knowledge. The main problem of induction is the identification of the suitable characteristics or attributes on which induction would be performed. Michalski and Chilausky (1980) compared two methods of knowledge acquisition in the context of developing soybean disease diagnosis through interviewing experts and formally representing their decision rules, and through inductively inferring the rules from examples of these experts' decisions using an inductive program AQ11 (Michalski and Larson, 1978). Two results were contrary to their expectations: (1) the inductive method required less effort and produced decision rules that were somewhat better than expert derived rules. They repeated their experiment several times, introducing modifications to the expert derived rules and trying different rule evaluation schemes. The same results were obtained, and (2) the inductively derived rules were viewed generally quite favourably by experts – with a few exceptions. They suggested that a procedure in which an expert would edit inductively derived rules, in conjunction with an approved inductive program, could lead to an attractive new method of knowledge acquisition and concluded that the inductive method for introducing knowledge to expert systems can be both useful and practical if the problem domain is sufficiently simple. Broner, King and

Nevo (1990) applied structured induction (Shapiro, 1987) in knowledge acquisition for a barley crop management expert system using the ID3 (Iterative Dichotomiser Tree) program (Quinlan, 1979).

**2.7.4.3 Interaction** – the knowledge acquisition problems have led AI people to seek out the solutions from other disciplines. Psychology was found to be helpful. Shaw and Gaines (1987) proposed an interactive knowledge elicitation technique using Kelly's (1955) personal construct psychology (PCP) and repertory grid techniques. They suggested that

> "PCP provides a model of human knowledge acquisition, representation, and processing that has been made operational through computer programs for interactive knowledge elicitation. These may be used in developing the expert's vocabulary and in encoding aspects of his reasoning for a ruled-base system."
>
> (Shaw and Gaines, 1987, p. 110).

Experts directly interact with an interactive computer program that helps them clarify their own thoughts, structure their knowledge, and identify and formalise their concepts. However, due to the nature of the theory, the results will be personal, i.e. very idiosyncratic. Two experts addressing the same problem may produce quite different sets of results (Hart, 1986). However, Gaines and Shaw (http://pages.cpsc.ucalgary.ca/~robertof/courses/679/Knowledge.html, 2003) show that the repertory grid technique can be used when several experts are involved. They assume people may use the same term for different distinctions, and different terms for the same distinction. Thus, four situations may arise through interaction between terminology and distinction (Figure 2.3) (http://ksi.cpsc.ucalgary.ca/articles/KBS/KER/KER7.html, 2003).

> "The recognition of *consensual* concepts is important because it establishes a basis for communication using shared concepts and terminologies. The recognition of *conflicting* concepts establishes a basis for avoiding confusion over the labelling of differing concepts with the same term. The recognition of *corresponding* concepts establishes a basis for mutual understanding of differing terms through the availability of common concepts. The recognition of *contrasting* concepts establishes that there are aspects of the differing knowledge about which communication and understanding may be very difficult, even though this should not lead to confusion. Such contrasts are more common than is generally realised. For example, it is possible to derive the same theorem in mathematics either by using an algebraic perspective, or a geometric one. There is nothing in common in these two approaches except the final result."
>
> (http://ksi.cpsc.ucalgary.ca/articles/ KBS/KER/KER7.html, 2003, p.1/3).

This implies that two experts may, for example, use different decision trees or production rules in diagnosing rice diseases, but still give the same results.

**Figure 2.3** Four-quadrant representations of consensus, correspondence, conflict, and contrast in the conceptual systems.

<table>
<tr><td colspan="2" rowspan="2"></td><th colspan="2">Terminology</th></tr>
<tr><th>Same</th><th>Different</th></tr>
<tr><th rowspan="2">Distinctions</th><th>Same</th><td>Consensus<br>People use terminology and distinctions in the same way</td><td>Correspondence<br>People use different terminology for the same distinctions</td></tr>
<tr><th>Different</th><td>Conflict<br>People use same terminology for different distinctions</td><td>Contrast<br>People differ in terminology and distinctions</td></tr>
</table>

**Source**: http://ksi.cpsc.ucalgary.ca/articles/KBS/KER/KER7.html (2003), p. 1/3

The methodologies for two experts are much the same as for individual experts, except for the need to track the terminology differences. A combined repertory grid from two experts can be produced by subtracting the values on one of the grids from the values on the other. As a result, the smaller values, or the values approaching 0, indicate similar constructs while the larger values, or the values deviating from 0, indicate dissimilar constructs (http://ksi.cpsc. ucalgary.ca/articles/KBS/KER/KER7.html, 2003).

The three basic approaches are commonly used in acquiring knowledge from experts. However, in the case that the expert and the knowledge engineer are separated like in this study, these approaches were deemed inconvenient. Besides these approaches, eliciting knowledge from other sources, such as textbooks, handbooks, and other documents written by experts, is another approach to acquire the experts' knowledge. Thus this approach was used in acquiring knowledge for the example expert system for rice disease diagnosis and management (POSOP) for use in this study. Documentary research was done to find out whether there are any textbooks, handbooks, and other documents of rice diseases. Fortunately, decision criteria for rice disease diagnosis (Table 2.3) are well documented in a handbook written by a Thai expert in rice diseases (Disathaporn, 1982).

### 2.7.5 Knowledge Representation

Expert systems derive their power from representations of human expert knowledge that is normally recorded or held in the human mind. A key to making computer systems improved problem solvers is to have them mimic the way humans' store, retrieve, and manipulate knowledge (Plant and Stone, 1991). The human mind, like other reasoning systems, faces the problem of storing knowledge in some type of memory, of retrieving the knowledge when required, and acting on the knowledge (Parsaye and Chignell, 1988).

The processes of storing, retrieving, and manipulating knowledge in an expert system is referred to as 'knowledge representation.' The goal is to carry out these functions in an efficient and effective manner (Luger and Stubblefield, 1993; Parsaye and Chignll, 1988). Knowledge can be organised and stored in the knowledge base in several different ways to facilitate fast inferencing or reasoning (Turban, 1993).

Over the past twenty-five years, numerous knowledge representation approaches have been developed and implemented (Luger and Stubblefiels, 1993). The common approaches include logics, rules, frames, production systems, scripts, and semantic networks (Lugger and Stubblefield, 1993; Parsaye and Chignell, 1988; Plant and Stone, 1991; Turban, 1993). Principally, these approaches have been developed to strengthen the effectiveness and efficiency of rule structuring and retrieval.

**Table 2.3** Decision criteria for rice disease diagnosis without visual aids.

| Causal Organism | Root | Stem | Leaf Sheath | Leaf Blade | Panicle | Disease Name |
|---|---|---|---|---|---|---|
| **Fungi** | Normal | Eye shape, grey-brown lesions, appears dried-burnt | | | Broken-folded | Blast |
| | Normal | Brown streak lesions | | | | Narrow Brown Spot |
| | Normal/ Abnormal and black | Round/oval brown spot lesions | | | | Brown Spot |
| | Normal | Grey-green lesions, appears dried | | | Wilted-dried | Sheath Blight |
| | Tillering at lower nodes | Abnormally long internodes | Pale | Abnormally narrow-long and pale | May/may not exist | Bakanae |
| | Normal | Brown-black strip lesions | | Mostly normal | Sunken in leaf sheath | Sheath Rot |
| | Normal | Weak | Normal | | Comprises infected seeds | False Smut |
| | Normal and black | Brown-grey-black spots/streaks lesions | | | | Dirty panicle |
| **Bacteria** | Normal/dead and rotted | Wilted-dried | | Dried at edges | Wilted-dried | Bacterial Leaf Blight |
| | Normal | Weak | Normal | Translucent and streaky lesions | abnormal | Bacterial Leaf Streak |

**Source**: Adapted from Disathaporn (1982), pp. 24-25

**Table 2.3** Decision criteria of rice disease diagnosis without vision aids (cont).

| Causal Organism | Root | Stem | Leaf Sheath | Leaf Blade | Panicle | Disease Name |
|---|---|---|---|---|---|---|
| **Virus and/or Mycoplasma** | Abnormally short-black | Stunted-pale | Abnormally narrow and short | Yellow-orange | Short | Yellow Orange Leaf Virus |
| | Normal/ Abnormal and black | Stunted-green | Abnormal | Twisted and dark green | Short- do not exist | Ragged Stunt Virus |
| | Normal or abnormal | Stunted-green | Galls on skin | Galls on skin, narrow and short | Short- do not exist | Gal Dwarf Virus |
| | Normal | Dead and standing | Orange | Orange, Leaf edges Folded inside | Do not exist | Orange Leaf Mycoplasma |
| **Nematode** | Knot | Pale-yellow | | | Immature/ Do not exist | Root-knot nematode |

**Source**: Adapted from Disathaporn (1982), pp. 24-25

These representations share two common characteristics. They can be programmed with existing computer languages and stored in memory, and they are designed so that the facts and other knowledge can be used in reasoning. This means the knowledge base contains a data structure that can be manipulated by an inference mechanism (engine) (see Figure 2.2) that uses search and pattern matching techniques to answer questions and draw conclusions (Turban, 1993).

Some expert system shells use two or more knowledge representation approaches, with considerable success being achieved by integrating frames and production-rule languages to form hybrid representation facilities that combine the advantages of both components (Turban, 1993). Thus production rules and frames, and their advantages and disadvantages, are discussed below.

#### 2.7.5.1 Production Rules

Production systems were developed by Newell and Simon (1972) for their model of human cognition. Basically, the idea of these systems is that knowledge is presented as 'production rules' in the form of condition-action pairs: IF this condition (or premise or antecedent) occurs THEN some action (or result, or conclusion, or consequence) will (or should) occur (Turban, 1993). For example, a simple rule can be expressed as:

IF a plant is stunted THEN the pathogen is a virus.

According to Turban (1993), rules can be viewed as a simulation of the cognitive behaviour of human experts, and they are not just a formalism to represent knowledge in a computer; but rather, they represent a model of actual human behaviour. Two types of rules – knowledge and inference – are common in expert systems. Knowledge rules, or declarative rules state all the facts and relationships about a problem. Inference rules, or procedural rules, on the other hand, advise on how to solve a problem given that certain facts are known. Inference rules contain rules about rules. These types of rules are also called meta-rules (rules that describe how the others rules should be applied or modified). They pertain to other rules (or even to themselves). For example, knowledge rules in rice disease diagnosis and management may look like this:

RULE 1: IF stem is stunted-pale AND
leaf blade is yellow-orange AND
leaf sheath is abnormally narrow and short AND
insect vector is green rice leafhopper.
THEN the disease is yellow orange leaf virus.

RULE 2: IF stem is stunted-green AND
leaf blade is twisted and dark-green AND
leaf sheath has swollen sheath veins AND
insect vector is brown planthopper
THEN the disease is ragged stunt virus.

RULE 3: IF stem is stunted-green AND
leaf blade is narrow and short and has galls on skin AND
leaf sheath has galls on skin AND
insect vector is zigzag leafhopper
THEN the disease is gall dwarf virus.

RULE 4: IF the disease is yellow orange leaf virus OR
the disease is ragged stunt virus OR
the disease is gall dwarf virus
THEN get rid of insect vector (s) and host plant (s).

Inference (procedural) rules may look like this:

RULE 1: IF the plant is stunted
THEN request the insect vector found in the field from the user.

RULE 2: IF any necrotic spot, streak, or strip lesion is found on any part of the plants
THEN request the user select the pictures that best describe the lesions observed.

The knowledge engineer separates the two types of rules, encodes, and stores them in a computer program. Knowledge rules are stored in the knowledge base, whereas inference rules become part of the inference engine.

Production systems comprise production rules, working memory, and a control. Such systems are useful as mechanisms for controlling the interaction between statements of declarative and procedural knowledge. Each production rule in a knowledge base implements an autonomous chunk of expertise that can be developed and modified independently of other rules. When combined and fed to the inference engine, the set of rules behaves synergistically, yielding better results than that of the sum of the results of the individual rules. In reality, knowledge-based rules are interdependent. Adding a new rule or modifying an existing rule may conflict with existing rules (Turban, 1993). Production rules have been used in many expert systems. For example, MYCIN, a classic expert systems for diagnosing meningitis and other bacterial infections of the blood and prescribing treatment (Buchanan and Shortliffe, 1984), and PLANT/ds, the first agricultural expert system for diagnosing soybean diseases (Michalski et al., 1983).

#### 2.7.5.2 Frames

Human beings have the important capability of interpreting new situations using knowledge gained from past experience. This ability allows knowledge to grow with each experience rather than start from the initial conditions in every case. For example, based on past experience, plants are expected to have roots, stems, leaves, flowers, fruits, and seed. These elements are defining characteristics which, when taken as a whole, constitute the understanding of 'plants'. Large mental collections of knowledge structures (or frames of reference) are maintained in the human mind. People include these expectations as default values for the corresponding characteristics (Rolston, 1988).

A frame, first introduced by Minsky (1975), is a structure for organising knowledge – with an emphasis on default knowledge (Rolstons, 1988; Lugger and Stubblefield, 1993). It includes all knowledge about a particular object. This knowledge is organised in a special hierarchical structure that allows a diagnosis of knowledge independence.

A frame is a relatively large chunk of knowledge about a particular object, event, location, situation, or other element. It describes the object in great detail. The detail is given in the form of 'slots' that describe the various attributes and characteristics of the object or situation. As in frames of reference, they provide a concise, structural representation of knowledge in a natural manner. An object is grouped together into a single unit called a frame. Thus a frame encompasses complex objects, entire situations, or a management problem as a single entity. The knowledge in a frame is partitioned into slots. A slot can describe either declarative knowledge or procedural knowledge (Turban, 1993) (Figure 2.4).

Conceptually, frames can be comparable to a conventional database. Each record and field are comparable to frames and slots. Data in each cell is comparable to the value in each slot. The relationships between frames, as expressed by parent frames or arrows, are comparable to a relational database concept.

#### 2.7.5.3 Advantages and Disadvantages of Production Rules and Frames

By themselves, production rules do not provide a totally effective representation facility in that they do not have adequately expressive power to define terms, and to describe domain objects and static relationships among objects. The major inadequacies of production rules are in areas that are effectively manipulated by frames. The frame provides a rich structural language for describing the objects referred to in the rules and a supporting layer of generic deductive capability about those objects that is unnecessary to explicitly deal within the rules. A system's production rules can be partitioned, indexed, and organised using frame taxonomies. With this capability, it is easier for both the domain expert to construct and understand rules, and the system designer to control when and for what purpose particular sets of rules are applied by the system (Turban, 1993). Clearly, the use of frames is desirable (Brule' and Blount, 1989). However, one of the difficulties with frame representation is the problem of accurately defining the default values for a frame. It may appear to most people that a tree is assumed to have leaves, but someone from the Pacific northwest may expect a tree to have needles in contrast to leaves (Rolston, 1988). Given different environments and experience, people develop different frames of reference although they mean the same thing. For example, a rule for ragged stunt virus can be expressed as:

IF stem is stunted-green AND leaf blade is twisted and dark-green AND
leaf sheath has swollen sheath veins AND insect vector is brown planthopper
THEN the disease is ragged stunt virus.

**Figure 2.4** Partial frame representations for a rice viral disease.

| **Frame: Rice Disease** | |
|---|---|
| **Parent Frame: Rice disorders** | |
| Slot: Fungal | Value: |
| Slot: Bacterial | Value: |
| Slot: Nematode | Value: |
| Slot: Mycoplasma | Value: |
| Slot: Viral | Value: |

| **Frame: Viral Disease** | |
|---|---|
| **Parent Frame: Rice disease** | |
| Slot: Yellow orange leaf virus (YOLV) | Value: |
| Slot: Ragged stunt virus (RSV) | Value: |
| Slot: Gall dwarf virus (GDV) | Value: |

| **Frame: Ragged Stunt Virus Symptoms** | |
|---|---|
| **Parent Frame: Viral Disease** | |
| Slot: Stem | Value: stunted-green |
| Slot: Leaf blade | Value: twisted and dark green |
| Slot: Leaf sheath | Value: swollen sheath veins |

| **Frame: Insect Vector** | |
|---|---|
| **Parent Frame: Viral Disease** | |
| Slot: YOLV | Value: green rice leafhopper |
| Slot: RSV | Value: brown planthopper |
| Slot: GDV | Value: zigzag leafhopper |

The advantages and disadvantages of production rules and frames are given in Table 2.4. Thus, hybrid knowledge representation was used in developing POSOP to make the best use of the combined advantages of both production rules and frames.

**Table 2.4** Advantages and disadvantages of production rules and frames.

| Approaches | Advantages | Disadvantages |
|---|---|---|
| **Production rules** | Simple syntax, easy to understand, simple interpreter, highly modular, flexible (easy to add to or modified). | Hard to follow hierarchies, inefficient for large systems, not all knowledge can be expressed as rules, poor at representing structured descriptive knowledge. |
| **Frames** | Expressive power, easy to set up slots for new properties and relations, easy to create specialised procedures, easy to include default information and detect missing values. | Difficult to program, difficult to inference, lack of inexpensive software, difficult to define default values |

**Source**: Adapted from Turban (1993), p. 570 and Rolston (1988), p.53

### 2.7.6 Evaluation of Agricultural Expert Systems

Evaluation of an expert system should not be left as an afterthought, but must be considered throughout the entire design and development process (Hollnagel, 1989). While many agricultural expert systems have been built, very few have been deployed in the farming community, and little effort has been directed at evaluating them (Brown, Walsh and Pfeiffer, 1992). Evaluation of an agricultural system involves verification and validation. Verification focuses on the software aspects of the system and is concerned with building the system correctly, whereas validation focuses on the model of the system itself and its correctness. Of these two activities, verification is by far the easier since there is an absolute standard of correctness against which the program can be compared. Validation is difficult, as expert systems are models of human knowledge and reasoning. Although they attempt to emulate human reasoning, they do not give complete or exact output. Since the search space is so large, or is incomplete, neither a computer nor a human can possibly solve these problems exactly and/or completely. Thus heuristics and incomplete knowledge are used to draw conclusions (Ostegard, 1990).

#### 2.7.6.1 Verification

An expert system must be checked for consistency and completeness. Checking for consistency includes detecting redundant rules, conflicting rules, rules that are subsumed by the other rules, unnecessary IF conditions, and circular-rule chains. Checking for completeness includes detecting un-referenced attribute values, illegal attribute values, an unreachable conclusion, and dead-end IF conditions (Ostegard, 1990; Perkins et al., 1989; Wright, 1992).

#### 2.7.6.2 Validation

In the early stage of development, an expert system may be checked for face validity by the human expert on which it is based (Harrison, 1991) or among a group of independent experts (Wright, 1992). This is a simple and quick approach to informal validation, which appears to be all that has been used on many systems (e.g., Roach et al., 1987). It provides a useful initial screening, but lacks power to identify weakness in a system. Once a more refined model is developed, more formal testing is desirable. Field testing by potential users, and use of the expert system in parallel with existing decision support systems, are desirable before a system is released for general adoption. Finally, allowance needs to be made for evaluations as part of product maintenance when a system is in commercial use (Harrison, 1991). Formal testing is discussed in Harrison (1991), Hollnagel (1989), Ostegard (1990), and Wright (1992).

## 2.8 Development of an Example Expert System (POSOP)

The proposed research looks at the extension agents' attitudes towards expert systems as decision support tools in Thailand. Extension agents' problems and needs are the first priority to be taken into account. Thus a preliminary survey and personal interviews on the needs of the extension agents for expert systems were conducted. Given the results, the agents made it clear disease diagnosis was the most needed area that expert systems can potentially help alleviate. Since rice is the most important economic crop in Thailand, an expert system for rice disease diagnosis and management (POSOP) are deemed meeting the agents' problems and needs.

In developing an example expert system (POSOP), at least six out of the eight factors proposed by Turban (1993) exist. These are (1) the system can preserve scarce human expertise so that it will not be lost, (2) expertise is needed in many locations, (3) the expertise will probably improve performance and/or quality, (4) the system can be used for training, (5) the system solution is likely to be available faster than a human's solution, and (6) the expert system is probably more consistent and/or accurate than humans. Whether the solution to the problem has a high payoff is not yet known.

It is expected that POSOP might be a new alternative decision support tool, or a tool for training novice extension agents or new experts, particularly where the scarcity of experts in the field is a problem, and the problem exists over many areas. In the near future, the problem of retaining human experts could be worse due to the impact of the early retirement policy, imposed by the $8^{th}$ (1997-2001) and the $9^{th}$ (2002-2006) National Economic and Social Development Plan (http://www. infonews.co.th/CSC/detail.htm, 1999; http://www.infonews.co.th/CSC/ june7.htm, 1999; http://www.businessworld/ ocsc.go.th/web/MainLink1.asp, 2004), on manpower in the public sectors including the Department of Agricultural Extension (DOAE). Furthermore, POSOP can be used in educational institutions, and its knowledge base can be modified to keep up with the advances in rice production knowledge.

Developing POSOP was part of this research, not a large-scale expert system development project. Hence, POSOP was developed by the researcher as a novice knowledge engineer, guided by relevant documents instead of acquiring and eliciting knowledge from expert (s). Thus, the knowledge base of POSOP was derived from textbooks and handbooks. Fortunately, decision criteria for rice disease diagnosis are provided in a handbook written by an expert in rice diseases (Disathaporn, 1982, pp. 24-25). Hybrid knowledge representation was applied to make the best use of the combined advantages of both production rules and frames in developing a hybrid system using both rule-based and framed-based systems. Once POSOP was verified, it was validated, (before using it as an example expert system in the proposed research), using face validity by obtaining comments from the rice disease expert in Thailand on which POSOP's knowledge is based. In POSOP-user interface, the concept of 'client-specialist' communication was adopted, and long question sessions without providing feeding back were avoided. Also, graphic user interface was used in obtaining the disease symptoms from users.

A shell software package, KnowledgePro for Windows version Gold 2.51 (Thompson and Thompson, 1991) was selected as the tool for developing POSOP, as it was claimed the strength of the language lies in its flexibility and the power of its combined object-oriented programming (OPP) and list processing capabilities. It also provides design tools for point and click design, debugging tools, a multi-document editor, lower level language access such as C, C++, or Pascal via Dynamic Link Library (DLL) and the Windows Application Program Interface (API) such as spreadsheets via Dynamic Data Exchange (DDE). It does not restrict to a pre-defined format or paradigm. Most importantly, it supports the Thai language and a graphical user interface.

POSOP was developed using the IDEAL methodology (Recio, Acuna and Juristo, 1999). It was designed for use by poorly skilled computer users as in the preliminary survey and the interviews the agents perceived themselves as poorly skilled computer users. It is an automatic system running from a CD drive, and provides a graphic user interface, user friendly system; it requires a computer with the WINDOWS operating system with 640K Ram, CD drive, mouse, a CGA (or EGA, or VGA) screen, and Hercules graphic card or compatible; and either Windows 98, XP, or NT. It diagnoses 15 important rice diseases in Thailand and provides recommendations on disease management (Appendix G).

## 2.9 Application of Expert Systems in Agriculture

Evans, Mondor and Flatan (1989) view expert systems as a technology suitable for solving problems in farm management for a number of important features. Firstly, the development process is incremental and exploratory in nature; hence, it aids in the formalisation of ill-structured and poorly understood problems. Secondly, explicit representation schemes make it easy to understand and modify knowledge; thus, changes to a developing system can be made much easier. Thirdly, through the use of extensive domain knowledge, only relevant information is considered and thus difficult problems can be reduced down to a manageable size. Finally, through the explanatory facility, explanations and justification for recommendations are provided. These decrease user scepticism and increase user confidence in the accuracy of the system's results.

In another view, Sullivan and Ooms (1990) believe that expert systems offer creative and pioneering opportunities for providing extension agents and farmers with the essential management and decision-making capabilities for their success far into the next century. Expert systems have the potential to increase each extension agent's expertise to the highest level attainable with current knowledge, and provide assistance in solving integrated management problems.

In contrast, Dreyfus and Dreyfus (1986) criticise expert systems, and indeed all of artificial intelligence, as something of a fraud in that, specifically, there is no evidence that any man-made computer system has ever demonstrated anything that remotely resembles human intelligence. It is not true that expert systems can capture human intuition or reasoning in any way. Plant and Stone (1991) argue that this criticism may well be true, but from the perspective of agricultural management, the shortage of experts in agriculture and the seriousness of the problems make the development of computer-assisted management tools imperative. Whether these tools actually are intelligent is irrelevant provided that they do the job. If the best available tool for some applications is the expert system, then it should be used.

Although expert systems have both pros and cons, many expert systems have been developed and applied in various domains ranging from agriculture, chemistry, computer systems, electronics, engineering, geology, information management, law, manufacturing, mathematics, medicine, meteorology, military science, physics, process control, to space technology (Waterman, 1986). Other areas include public administration (Snellen, van de Donk and Baquiast, 1989), auditing (Dijk and Williams, 1990), finance (Edwards and Connell, 1989), urban planning (Kim, Wiggins and Wright, 1990), management and finance (Klein and Methlie, 1990), finance and accounting (Thierauf, 1990), investment management (Trippi and Turban, 1990), business (Lyons, 1994), and tourism marketing (Moutinho, Rita and Curry, 1996).

Applications of expert systems in agriculture have been dominated by crop pest and disease management, financial advice on the basis of accounts, environmental control of glasshouses, livestock shades, grain storage and drying facilities, (Webster and Amos, 1987), integrated crop management decision aids which encompass irrigation, nutritional problems and fertilisation, weed control and herbicide application, and insect control and insecticide use. Additional areas of potential and use are plant pathology, salinity management, crop breeding, animal pathology, and animal herd management (McKinion and Lemmon, 1985). Through the rapid development of advanced computer information, communication technology, as well as the competitive costs of hardware and software, expert systems in agriculture can be efficiently developed to assist decision makers in a wide variety of complex decisions.

Since problems in agricultural management routinely become highly complex, the possibility of fusing knowledge from different domains might be an advantage (Doluschitz and Schmisseur, 1988; Hochman et al., 1995), and as knowledge acquisition frequently creates bottlenecks in expert system construction, these limitations might sensibly lead to the development of integrated expert systems that integrate an expert system with statistical, numerical, database management and other utilities to produce a complete management decision support package (Jones, 1989; Plant, 1989b; Hochman et al., 1995). For example, COMAX, the first integration of an expert system with a simulation crop growth model (GOSSYM) (Lemmon, 1986).

It is useful to consider the current situation of practical applications of agricultural expert systems. Some are presented in Table 2.5. The first agricultural expert system, PLANT/ds, a system that diagnoses soybean disease in Illinois, was built on a mainframe using the PASCAL language by a computer scientist (Michalski et al., 1983). Other systems have followed. As computer technology advanced, the later systems have been developed on IBM PCs using various shells or combining shell(s) with a language.

To date, expert systems are successful to some extent (Table 2.5). Most are successful in validation e.g., PLANT/ds, Grain Marketing Analysis, FinARS, SOYBUG, SMARTSOY, CALEX/Cotten, CROPLOT, ESIM, FARMSYS, PLASMO, Wean, Drench, and Surplus. Some are successful with respect to potential users' acceptance (e.g., POMME, EXPERT/R, MISTING, and CORAC), and some users believe in the positive values of the systems (e.g., COMAX, Wean, Drench, and Surplus). From a commercial viewpoint, very few could be considered to be successful with only BEE AWARE available commercially for minimal cost, though it is difficult to determine worldwide usage from the literature.

## 2.10 Conclusions and Discussion

This Chapter contained a discussion on definitions of experts, expertise, and expert systems, how experts think, process information, make judgements and decisions. The analogy between human experts and expert systems, the structure and properties of expert systems, and the difference between expert systems and conventional computer programs were all discussed.

It is clear there are several factors necessary to consider before developing an expert system besides having a knowledge engineering methodology to build the system. These include the justification for the system, tools available, and the people involved. Furthermore, knowledge acquisition, knowledge representation, and system evaluation must all be given careful consideration. These factors are taken into account in developing an expert system for rice disease diagnosis and management (POSOP) for use as an example expert system in this study.

**Table 2.5** Some agricultural expert systems.

| System Name | Computer | Language/ Shell | Function | Goal/Objective | Success | Reference |
|---|---|---|---|---|---|---|
| PLANT/ds | Mainframe | PASCAL | Diagnoses soybean diseases | Provide interpretation and data advice | 70% agreement rate with experts | Michalski et al., 1983 |
| EXPERT/R | - | - | Diagnoses reproductive problems in dairy cattle | Provide reproductive consultation with dairy farmers | Preliminary well-accepted by county agents | Levin and Varner, 1987 |
| POMME | - | - | Recommends treatment of winter injuries, drought control, and multiple insect problem in apple | Help apple orchardists manage their orchards | Approved by extension experts | Roach et al., 1987 |
| Grain Marketing Analysis | IBM | Personal Consultant | Recommends best grain marketing alternatives | Test application of an expert system to grain marketing analysis | Compared favourably with expert's rankings | Thieme et al., 1987 |
| FINDS | - | - | Recommends farm machinery that can increase farm profit | Select machinery for whole-farm cropping systems for better profitability | - | Kline et al., 1988 |
| PEST | - | - | Identifies insect pest and recommends suitable control strategies | Investigate knowledge engineering techniques | - | Pasqual and Mansfield, 1988 |
| SMARTSOY | IBM | INSIGHT 2+ | Recommends management practices to control soybean insect pests | Increase profit for soybean farmers in area | 80% agreement rate with experts | Bachelor et al., 1989 |

**Table 2.5** Some agricultural expert systems (cont.).

| System Name | Computer | Language/ Shell | Function | Goal/Objective | Success | Reference |
|---|---|---|---|---|---|---|
| SOYBUG | IBM | INSIGHT 2+ | Recommends management practices to control soybean insect pests | Investigate knowledge acquisition techniques | Provide better recommendations than extension bulletins | Beck, Jones and Jones, 1989 |
| FinARS | IBM | INSIGHT 2+ | Evaluates overall financial health of farm business | Aid financial analysis and diagnosis | Results high correspondence with two experts | Boggess, van Blockland and Moss, 1989 |
| Misting | IBM | - | Controls setpoints for frequency and duration of misting in greenhouses | Provide autonomous dynamic controller for growers | Successfully followed the grower strategy | Jacobson et al., 1989 |
| COMAX | IBM | GCLisp | Recommends fertiliser and irrigation schedules for cotton | Provide management practices for cotton production | Farmers estimated value of system at $100-350/ha | McKinion et al., 1989 |
| CALEX/Cotton | IBM | C | Provides schedule of upcoming crop management activities | Provide access to the accumulated knowledge of the Californian cotton production system | Compared reasonably to expert's | Plant, 1989a; Plant, 1989b |
| FLEX | IBM | C and CLIPS | Recommends key strategies and tactical decision throughout the calendar year | Provide farm level decision support for cotton farmers | - | Stone and Toman, 1989 |
| CIRMAN | - | - | Recommends and explains crop insurance strategies | Aid selecting crop insurance strategies based on whole-farm | - | Helms, et al., 1990 |
| FEEDBAL | IBM | ADVISOR-2 and PROLOG-2 | Calculates whole farm forage budgets specific to an individual property | Improve management for mix-farming and grazing property | - | Lodge and Frecker, 1990 |

**Table 2.5** Some agricultural expert systems (cont.).

| System Name | Computer | Language/ Shell | Function | Goal/Objective | Success | Reference |
|---|---|---|---|---|---|---|
| CROPLOT | IBM | Rabbi | Recommends suitable crops to given plots | Make better decision in crops allocation | 90% agreement with experts | Nevo and Amir, 1991 |
| ESIM | - | CLIPS | Decides water management in an irrigation project | Investigate knowledge engineering techniques | Improved water management decision | Srinivasan, Engel and Paudyal, 1991 |
| FARMSYS | IBM | PROLOG | Estimates crop production, gross revenue, and net profit for individual field and for the whole farm | Evaluate operational behaviour of a farm system | Qualified rate by a team of experts | Lal et al., 1992 |
| CAES | - | - | Identifies main cereal aphid species in Spain and control measures | Help non-aphid specialist to obtain accurate identification | Currently running in Videotext allowing for consulting via a telephone line throughout Spain | Gonzalez-Andujar, Garcia-de Ceca and Fereres, 1993 |
| BEE AWARE | - | - | Diagnoses and manages honey bee diseases, pests, parasites, and predators | Test a new means of transferring up-to-date information to beekeepers | Available commercially for minimal cost | McClure, Tomasko and Collison, 1993 |
| CORAC | IBM | - | Estimates expected impacts of downy mildew, warns date of weevil and the first attack of aphid on hop fields, and indicates the need for treatment | Control hop protection | - | Mozny, Krejci and Kott, 1993 |

**Table 2.5** Some agricultural expert systems (cont.).

| System Name | Computer | Language/ Shell | Function | Goal/Objective | Success | Reference |
|---|---|---|---|---|---|---|
| PLASMO | - | - | Identifies fungicide application time based on actual downy mildew development | Forecast downy mildew development in grapevine. | Good correlation between field observations and model simulation infections | Rosa et al., 1993 |
| Weed Adviser | IBM | Personal Consultant ™ Plus | Identifies weed and offers alternative control measures, indicates treatment and herbicide | Help extension worker select weed control strategies | - | Pasqual, 1994 |
| Wean | IBM | KnowledgePro | Recommends whether to wean for a group of ewes and lambs | Aid weaning lamb decision | 84% agreement on advice and explanations rate with farmers and farmers believed benefit at $3,100 | Nuthall and Bishop-Hurley, 1996a; Nuthall and Bishop-Hurley, 1996b |
| Drench | IBM | KnowledgePro | Recommends whether to drench a group of ewes or lambs | Aid sheep drenching decision | 80% agreement on advice and 76.2% on explanations rate with farmers and farmers believed benefit at $1,800 | Nuthall and Bishop-Hurley, 1996a; Nuthall and Bishop-Hurley, 1996b |
| Surplus | IBM | KnowledgePro | Recommends when to close pasture for conservation and surplus feed allocation strategy | Aid pasture conservation and surplus feed allocation | 88% agreement on advice and 94% on explanations rate with farmer and farmers believed benefit at $2,300 | Nuthall and Bishop-Hurley, 1996a; Nuthall and Bishop-Hurley, 1996b |

**Table 2.5** Some agricultural expert systems (cont.).

| System Name | Computer | Language/ Shell | Function | Goal/Objective | Success | Reference |
|---|---|---|---|---|---|---|
| VEGES | IBM | - | Diagnoses and treats pests, diseases, and nutrients disorders of 6 greenhouse vegetables in Mediterranean area | Develop high technology software applicable to low technology Mediterranean greenhouse industry | - | Yialouris et al., 1997 |
| EXSYS | - | PROLOG | Diagnoses iris flower bulb, diseases, pests, and non-parasitic disorders in the Netherland | Retain expertise and make it more generally accessible | 65% error-free diagnosis | Kramers, Conijn and Bastiaansen, 1998 |

**Source:** the various journals quoted

To date expert systems have been developed and applied in various domains including agriculture. Still, agricultural expert systems are not being readily accepted by their potential users (Adoum, 1992; Greer et al., 1994; McCown, 2002). It seems the integration of technology in an organisation was more of a social change process than a technical problem (Mincemoyer, 1990). Thus, the emphasis in this research is on the human elements of expert systems use.

# CHAPTER 3

# Adoption of Innovations and Agricultural Expert Systems

## 3.1 Introduction

Expert systems are used mainly as extension tools in contrast to research activity. Their extension role presents several fundamental obstacles to their successful adoption in agriculture. A simulation model can be considered a success if it adequately performs its simulation function. However, expert systems must be judged by higher standards. They cannot be considered successful just because of correct mimicking as they must also be employed by at least some of the potential users (Plant and Stone, 1991).

As with other agricultural technology innovations, expert systems are created to be used by their potential users – extension agents and farmers. However, expectation and reality may not always meet each other. The fact is that in the past the use of expert systems, and decision support systems, has been low (Adoum, 1992; Greer et al., 1994; McCown, 2002).

Expert systems are less than two decades old; their application to agriculture began in the early 1980s and became an important issue between the late 1980s and the early 1990s. Not surprisingly, the field has suffered from development difficulties and setbacks, and much still needs to be learned (Plant and Stone, 1991). Lessons learned from the adoption of other technological innovations might be relevant to the adoption of expert systems.

This chapter contains a review of the adoption of innovations, definitions of innovations, and of the adoption process and adopter categories. As a computer program, an expert system clearly requires a computer, thus a successful case history of computer adoption by extension agents is also reviewed. Although not specifically addressing issues directly relating to extension agents' adoption of expert systems, the review will provide a basis for considering extension agents' adoption of innovations, and the adoption of expert systems in particular. Lastly, the adoption of agricultural expert systems and factors influencing the adoption of agricultural expert systems – expert system attributes and support of the system by institutions, as well as user characteristics – are all discussed.

## 3.2 Adoption of Innovations

### 3.2.1 Definition of an Innovation

Rogers (1995, p.11) defined an innovation as "an idea, practice, or object that is perceived as new by an individual or other unit of adoption." Ban and Hawkins (1996, p. 96) extended the meaning of newness and defined an innovation as "an idea, method or object which is regarded as new by an individual, but which is not always the result of recent research." For instance, the metric system is still an innovation for some Anglo Saxon North Americans even though it was developed 200 years ago. Bayer and Melone (1989), cited in Jangu (1997, p. 11), argued that "an innovation can be a new idea such as structured programming, or a new hardware technology." They pointed out that "Not all innovations are single items, they may be part of interdependent technology." Similarly, Rogers (1983) and Ban and Hawkins (1996) argued that most technology innovations have two components – hardware and software. The technology embodied in the tools as material or physical objects comprises the hardware, and the knowledge base for the tool comprises the software. This is clear in the case of a computer where the machine (hardware) is useless without the programs (software) which instruct it what to do. It also holds true for a plant variety where the plants are equivalent to hardware and the techniques for growing them are equivalent to software. While a technology innovation serves to reduce one type of uncertainty concerning the cause-effect relationships that are involved in attaining a desired goal, it also creates another kind of uncertainty because of its newness to the individual, and motivates him/her to seek information on how the new technology can be evaluated. This is called 'innovation-evaluation information'; it serves to reduce the uncertainty about the expected outcomes of an innovation (Rogers, 1995).

### 3.2.2 The Adoption Process

> "People ordinarily do not accept new ideas or practices immediately upon hearing about them. The time from initial knowledge to final acceptance may range from a few days to many years. Also, a decision to change is ordinarily the product of a sequence of events and influences operating through time rather than an abrupt metamorphosis."
>
> (Lionberger, 1960, p. 21).

A review of research studies (Lionberger, 1960) has demonstrated clearly that extensive delays often occur between the time farmers first hear about favourable innovations and the time they adopt them. A classic example is the adoption of hybrid seed corn in Iowa; it took six years on average for the first 6 percent to adopt, with over 80 percent adopting in the next 6 years (Ryan, 1948; cited in Lionberger, 1960). Researchers have been keen to find out what happens during this time. The following stages are often used to analyse this adoption process (Ban and Hawkins, 1996; Lionberger, 1960; Rogers and Shoemaker, 1971):

**(1) Awareness** – an individual first hears about the existence of the innovation; he/she has only general information about it. He/she knows little or nothing about its special features, its potential usefulness, or how it would likely work for him/her.

**(2) Interest** – an individual develops an interest in the innovation that he/she has heard of. He/she is not satisfied with only knowing that it exists and is curious to find out more additional information about what it is, how it will work, and what it will do. His/her curiosity motivates him/her to actively seek the information desired, and to listen, read, and learn more about it.

**(3) Evaluation** – an individual weighs the information and evidence accumulated in the previous stages. He/she makes a mental application of the innovation after consideration of its pros and cons, applies it to his/her own situation, anticipates future situations, and decides whether or not to try it. To be sure, evaluation occurs at all stages of the adoption process, but it is most evident at this stage, and perhaps most needed here.

**(4) Trial** – an individual is confronted with a distinctly different set of problems. He/she actually tests the innovation on a small-scale experiment. This means that he/she must learn how, when, where, and how much to put the innovation into practice. Competent personal assistance may be required in putting the innovation to use. If the small-scale trial proves successful, he/she then makes large-scale use of it.

**(5) Adoption** – an individual decides that the innovation is good enough for full scale and continued use. A complete change is made with that end in view.

It is not necessary that all decisions include a clear-cut 5-stage sequence. Many decisions in practice are made simply on the basis of habit or tradition, or at least without extended deliberation. Also, the decision process can be truncated at any point, or stages may be so blended that it is impossible to make distinctions between the stages. Furthermore, after final adoption any issue may be reopened for consideration and the whole process started again (Lionberger, 1960). Also, the process depends on the nature of the innovation, for example, some innovations are easy to try out on a small scale (e.g. new improved varieties, new practices). Others are not (e.g. a tractor, a combine machine).

In the past, diffusion researchers were in favour of this adoption process model. However, it has been criticised for being too simple. Among its various deficiencies are: (1) it implies that adoption is always the end of the process whereas in reality either adoption or rejection may be a likely outcome. Thus, a neutral term that allows for either outcome is needed; (2) the five stages do not always take place in the specified order, and some of them may be skipped, particularly the trial stage. Evaluation actually occurs in all stages, rather than just at the evaluation stage; (3) adoption is seldom the end of the process, as post-adoption information seeking may occur (Mason, 1964; cited in Rogers and Shoemaker, 1971) to confirm or reinforce the decision, or the individual may later change from adoption to rejection or vice versa (Rogers, 1983; Rogers and Shoemaker, 1971).

Some critics of the adoption process model conclude that there is insufficient evidence to prove the existence of these stages. Decision-making in practice may be much less rational and systematic (Ban and Hawkins, 1996). Only two stages are necessary and sufficient –

awareness and adoption - with awareness always taking place before adoption (Rogers and Shoemaker, 1971).

In a study, Pannell (1998) argues that three broad conditions are necessary for adoption of a farming-system innovation by an individual farmer. These are awareness of the innovation, perception that it is feasible and worthwhile to trial the innovation, and perception that the innovation promotes the farmer's objective.

Adoption theory in agriculture essentially sees the decision to adopt or reject an innovation as a risky choice problem. It is risky because the farmer is not sure whether he/she will be better or worse off by adopting. The possibility of making a correct, or incorrect, decision clearly depends on the farmer's knowledge of the relevant parameters – the more that is known the less likely it is that an incorrect decision will be made. Thus, adoption is essentially a dynamic learning process of collecting information, revising opinions or attitudes and reassessing any decision (Marsh. 1998).

Similarly, Pannell (1999) emphasises that adoption is a process involving collection, integration and evaluation of new information. In other words, it is a process in which risk declines steadily over time. In beginning of the process, the quality of decision-making may be low as uncertainty is very high. As the process progresses, better decisions can be made as uncertainty becomes less. Viewed in this light, the adoption process never ends, in the sense that uncertainty reaches zero. All options are continuously open to question and review, as new information becomes available and/or circumstance change.

### 3.2.3 Adopter Categories

According to Rogers (1983) members of a social system can be classified on the basis of innovativeness, that is the degree to which an individual, or other decision unit, is relatively early in adopting new ideas relative to other members of a system. The adoption of an innovation follows a normal, bell-shaped curve when plotted over time on a frequency basis, or an S-shaped curve when the cumulative number of adopters is plotted. One reason is the diffusion effect, defined as the cumulatively increasing degree of influence upon an individual to adopt or reject an innovation resulting from the activation of peer networks about the innovation in the social system. This influence results from the increasing rate of knowledge and adoption, or rejection, of the innovation in the system.

The continuum of innovativeness can be partitioned into five adopter categories on the basis of a normal distribution: innovators (2.5%), early adopters (13.5%), early majority (34.0%), late majority (34.0%), and laggards (16.0%). These five categories are conceptualisations based on observations of reality which are designed to make comparisons possible. Dominant attributes of each category are: innovators-venturesome; early adopters-respectable; early majority–deliberate; late majority-sceptical; and laggards-traditional (Lamble and Seaman, 1993; Rogers, 1983; Roger and Shoemaker, 1971).

**(1) Innovators** – noted as venturesome. They are very eager to try new technologies. Their interest leads them out of their local circle of peers and into a more cosmopolitan social relationship. They tend to communicate and make friends with other innovators who may be spread over great geographical distances. Innovators tend to underconform to the social norms of the local community. Therefore, although they may have high social status, they may not be respected as opinion leaders. They have the psychological and financial ability to assume the risk involved in being the first to try new technologies. They are capable of understanding and applying complex technical knowledge. Innovators play a significant role in a social system by introducing new technologies from outside to the social system. In terms of computer technology, they tend to be the first people who own and use computers.

**(2) Early Adopters** – regarded as respectable. These are the next 10 to 15 percent to adopt. They are a more integrated part of the local social system than innovators. As with innovators, early adopters have high social status. However, they are respected and possess a great deal of opinion leadership. They serve as role models, tend to be successful in implementing new technologies, and are therefore often viewed as the people to check with before using a new technology. Early adopters tend to have the greatest amount of contact with local extension agents and are very important to the success of these agents.

**(3) Early Majority** – described as deliberate. These represent the approximately 33% of the population who adopt just before the average member. They may deliberate for some time before completely adopting a new technology. Although they are rarely in opinion leadership positions, they are regarded as 'doers' or 'action leaders' who interact frequently with peers and provide an important link in the diffusion process between the early adopter and the late majority.

**(4) Late Majority** – noted as sceptical. These people represent one third of the population who adopt just after the average member in the social system. They are imposed by economic necessity and increasing social pressures to adopt a new technology. Because they have relatively limited resources, they are only convinced after most of their peers have adopted.

**(5) Laggards** – characterised as traditional. These are the last 15 percent to adopt. They are oriented to the past. Their decision-making is based on what was done in the past. They are the most localite (likely to communicate only inside their social system) of all adopters. They tend to contact primarily with others who also have relatively traditional values – some may be near-isolates. Laggards are often suspicious of innovations, of innovators, and change agents. While laggards may be the group in greatest need of extension assistance, they are probably the most difficult group for extension agents to work with. The term 'laggards' has been criticised as these people might in fact be doing the right thing with respect to *their* objective. Some would say they are rational – all the above discussion assumes that innovation is 'good' for *all* people.

### 3.2.4 Adoption of Computers by Extension Agents

As mentioned earlier most technology innovations have two components – hardware and software. As expert systems require a computer it is important to note, as would be expected, there is clear evidence that the use of management information systems appears to be positively correlated with computer adoption (Lippke and Rister, 1992). This indicates the trend towards computerised management information systems adoption. Thus, it is useful to consider successful case histories of computer adoption by extension agents.

These might reveal obstacles to be overcome in having more extension agents participating in agricultural information systems and expert systems.

Mincemoyer (1990) applied the adoption process to large-scale adoption and use of computers by Pennsylvania Cooperative Extension Service. They achieved a great deal of success in adopting and using computers throughout the extension organisation. He noted that

> "...the true impact of technology on extension has been alarmingly low...the main reason for these poor results is that goals of the technology leaders have been directed toward the technology, not toward the users. It is the establishment of, and achievement of, user-oriented goals that defines true success in computer adoption."
>
> (Mincemoyer, 1990, p. 40)

Mincemoyer's study indicated that the adoption process and adopter categories of the extension agents and the farmers' were similar in terms of the adoption stages (awareness, interest, evaluation, trial, and adoption), adopter categories (innovators, early adopters, early majority, late majority, and laggards), and their ratios in the population. The total population of extension agents was divided according to the adopter categories and special attention was first focused on those identified as the early adopters. Special sub-projects were set up and the early adopters were included in these groups. This created interest among the early adopters and encouraged them to actively use their influence to encourage others, especially members of the early majority, to be involved in computerisation activities. However, special attention was not restricted to the early adopters. To achieve the goal, most members of the late majority needed to become involved. Thus, effort was made to refine instructional approaches and gather numerous success stories to specifically spark the interest of members of the early and late majority. The focus then turned to making them successful adopters during periods of evaluation and trial.

The concern about computer technology adoption was the stages that all individuals went through, regardless of their category, to reach adopter status. The critical factor in each stage was that different information and education was required. It seems adoption projects must be structured to meet individuals' information and education needs to move them through all the stages. For instance, a computer project could stagnate if the individuals who were ready to trial and implement computer integration did not in fact have access to the required hardware and/or software. Mincemoyer (1990) concluded that the integration of technology was far more of a social change process than a technical problem, and that the adoption process can be directly applied to a technical project where user adoption is the goal. The adoption process should also lead to a focus on users and their needs.

### 3.2.5 Conclusions and Discussion

Although extension agents play an important role as change agents, little research on extension agents' adoption of innovation has been conducted. There is evidence supporting the idea that extension agents' adoption process and adopter categories are similar to the farmers'. Combining the knowledge of adopter categories in the population and the adoption stages for individuals might be applicable to other software adoption projects (e.g. expert systems). However, farmers' and extension agents' adoption of computers or expert systems might be different in terms of their education level, training support, objectives, and risk-taking. Generally, extension agents have a higher formal education level than farmers. In addition, they are attached to an organisation so that they are likely to have better training support assuming their organisation requires them to have good computer skills as part of improving extension service efficiency. These training expenses are absorbed by the organisation so that extension agents do not take personal risks in computer hardware and software investments. These factors are in sharp contrast to the farmers' situation where the farmers take risks and the full responsibility for the computer hardware and software investment. These ideas may also apply to the adoption of expert systems and are discussed in the following section.

## 3.3 The Adoption of Agricultural Expert Systems

Expert system technology provides the opportunity to deliver both information and expertise to extension agents (Offer, 1992; Sullivan and Ooms, 1990) as well as enhances the agents' performance on decision-making (Rafea and Shaalan, 1996). In addition, it provides institutional memory. The knowledge accumulated during years of field experience by extension experts is often poorly documented and tends to be lost when the individual retires. Expert systems are immortal, allowing preservation of valuable heuristic knowledge (Broner, Parente and Thompson, 1992). Still, agricultural expert systems are not being readily accepted by their potential users (Adoum, 1992; Greer et al., 1994; McCown, 2002).

As mentioned earlier, the study of expert systems is a rather young field. Most research carried out on agricultural expert systems appears to be in the development stages. Little research has directed at the adoption of the systems by their potential users – extension agents and farmers.

### 3.3.1 Factors Influencing the Adoption of Agricultural Expert Systems

Lack of acceptance has long been an impediment to the success of new information systems. The goal of most organisationally based information systems is to improve performance on the job (Keil, Beranek and Konsynski, 1995), and to increase productivity (Davidson and Voss, 2002). Clearly, performance impacts are lost whenever systems are rejected by users as no information technology system can increase productivity where users do not engage with it. User acceptance is a pivotal factor.

Acceptance of an agricultural expert system is likely to be influenced by a number of factors including: the attributes of the systems themselves, the support of the systems, and the users' characteristics. Understanding the factors influencing acceptance is crucially important for strategic planning aimed at a greater uptake of the technology.

#### 3.3.1.1 Expert Systems Attributes

Clearly, to be successful, a system must deal with significant problems (Travis and Latin, 1991) that respond to the potential users' needs (Adoum, 1992; Kamp, 1999); it must be accurate and reliable (Travis and Latin, 1991; Hochman, Pearson and Lichfield, 1994); its solutions must be quickly and readily available (Wolak and Carton, 1992), and it must be easy to use (Adoum, 1992; Travis and Latin, 1991). Even the most powerful expert system will not be applied if it requires too much effort on the part of the user (Berry and

Broadbent, 1987). For this reason, it is important to make the system as easy for the user to operate as possible.

In addition, the interface of an expert system (Evans, Mondor and Flatan, 1989), the part of an expert system that interacts with the user (Travis and Latin, 1991), is regarded as a critical factor in its acceptance by extension agents and farmers (Broner, Parente and Thompson, 1992; Hockman, Pearson and Litchfield, 1994; Nuthall and Bishop-Hurley 1996a, Wolak and Carton, 1992) (see Section 2.5). Whether or not an expert system achieves success may be determined by the nature of its user interface.

### 3.3.1.2 Support of a System by the Institution

Apart from the system attributes and user characteristics, the use of an expert system may depend on the 'access condition'. These include the availability of resources: an infrastructure to provide hardware and software updates, a training program to teach computer and expert systems skills, and help for the user's problems (Travis and Latin, 1991).

Mutscheler and Hoefer's (1990) studies on factors affecting the use of computer technology in human service organisations, although not specifically addressing issues relating to expert systems, provided a framework on the adoption of technology that may be applicable to computer use technology. As such, it can be applied to expert systems. The study was based on a survey of 60 human service administrators, managers and direct service practitioners who participated in a three-phase workshop. They found that practioners' attitudes towards a computer did not determine the actual use of the computer, but rather that the amount of training and ease of access were the most important factors related to computer use. In addition, availability of resources had a significant impact on computer use. They concluded that if human service agencies wanted to introduce computers, or other innovations, sufficient training and ease of access to the technology must be provided to users, professionals should be involved in the development of the information systems, and attention must be paid to the structural factors of the organisation, such as the availability of hardware and software, that could facilitate or impede the adoption of a new technology.

The conclusions seem to have provided a framework for the design and implementation of computing technologies in a human service. Thus, when an expert system is introduced to human service agencies, such as the Department of Agricultural Extension, these factors need to be taken into account. Furthermore, the Department of Agricultural Extension is more likely to absorb the training and support costs if it perceives that expert systems are useful in improving the performance of its personnel and the efficiency of extension services.

#### 3.3.1.3 User Characteristics

A limited amount of research on demographic and socio-economic characteristics of expert systems users (Adoum, 1992; Nuthall and Bishop-Hurley, 1996b) has been conducted. The findings provide a fundamental understanding of the characteristics of the potential users. However, it has become increasingly clear that perceived usefulness and ease of use are the two variables long recognised as key to user acceptance of information systems, the former is by far the more important (Davis, 1993; Keil, Beranek and Konsynski, 1995). This finding provided a rationale for redirecting efforts to explain information technology adoption. The shift was from computer uptake and computing expertise to what an expert system as a decision support tool offers the users, and its usefulness in improving decision-making and alleviating problems.

An old saying, 'Beauty is in the eyes of the beholder' may be re-phrased as 'Usefulness is in the eyes of the beholder.' What expert system developers perceive as potentially useful to users may not, in fact, be useful as perceived by the users. The users' perception of the system's value as an alternative decision support tool, therefore, is likely to be a crucial factor influencing the acceptance of the system. Unfortunately, less effort has been made to investigate this factor.

## 3.4 Conclusions and Discussion

The adoption of expert systems appears to depend on the system attributes, the support of the systems, and user characteristics. Clearly, the usefulness of the systems as perceived by the users and specific system attributes such as utility, accuracy, reliability, efficiency, ease of use, and user interface play an import role in an expert system's acceptance.

The acceptance of an agricultural expert system, at least among extension agents, may be significantly hampered by a lack of support from the organisation in the form of access to hardware and software, and training in using the systems. On the other hand, the adoption of an agricultural expert system by farmers appears to be an individual effort. Training and support costs have to be covered by the farmer.

While most research studies would suggest the extension agents' perceptions of the value of the system are an important influence on their attitudes towards the use of systems, the factors influencing the perception of value, which are thought to be the user's psychological characteristics, such as personality and intelligence, have not been studied.

Integration of a new technology with an organisation is a complex process. Focusing on only one factor e.g. the expert systems' attributes, or the institutional support, or user characteristics may not provide an adequate understanding of the problem as a whole. Thus this research focused on the holistic view of the problem by integrating all these factors in a framework through developing an operational model of extension agents' attitude towards the use of an example expert system (POSOP). The more basic background theories that provide an integrated framework are reviewed and a conceptual model of extension agents' attitudes towards the use of an expert system is presented in the next chapter.

# CHAPTER 4

# Background Theories and Conceptual Framework

## 4.1. Introduction

> "Over the past 2 decades, expectancy-value formulations of attitudes have met with considerable success in predicting the influence of attitudes on behavioral intentions and behavior. Two general models – the theory of reasoned action [TRA] (Ajzen and Fishbein, 1980; Fishbein and Ajzen, 1975) and the theory of planned behavior [TPB] (Ajzen, 1985) – have been responsible for generating most of the research on attitude-behavior consistency issues."
>
> (Manstead and van der Plight, 1998, p. 1313).

The two models both provide parsimonious explanations of the impact of information and motivation on behaviour. The models imply that people carefully consider available information before they make behavioural decisions, and thus they are considered by some (e.g., Conner and Armitage, 1998) as deliberative processing models.

According to Ajzen (1996), in Fishbein and Ajzen' s (1993) study on research based on the theories of reasoned action and planned behaviour, over 250 empirical researches based explicitly on the two models were identified. Although there have been numerous studies based on the TRA and the TPB, most research has focused on the accuracy of the models' predictability rather than the accuracy of the models' explanation of the psychological processes that underlie people's attitudes and behaviour (Manstead and van der Pligt, 1998). A meta-analysis of research using the two models revealed that on average they both explained between 40% and 50% of the variance in the intention, and between 19% and 38% of the variance in the behaviour (Sutton, 1998). Similarly, a recent meta-analytic review of the TPB efficiency, using 185 independent studies published up to 1997, revealed the TPB explained 39% and 27% of the variance in intention and behaviour, respectively (Armitage and Conner, 2001).

In an attempt to explain the processes underlying the extension agents' attitudes towards the use of an expert system, and towards its features, the TRA and TPB models are critically discussed. This discussion covers strengthening behaviour predictability by considering models and theories using psychological variables that might be usefully added to the model to enable a better understanding of the psychological processes underlying extension agents' attitudes and behaviour. The variables include personality traits (Matthews and Deary, 1998), and those related to the Triarchic Theory of Human Intelligence (Sternberg, 1985, 1988). Finally, a conceptual model of the attitudes of extension agents towards the use of an example expert system (POSOP) is presented.

## 4.2 The Theory of Reasoned Action (TRA)

"The Theory of Reasoned Action (Ajzen and Fishbein, 1980; Fishbein and Ajzen, 1975) is regarded as an important model of volitional behaviour in social psychology" (Orbell, Hodgkins and Sheeran, 1997, p. 945). It assumes that people are normally quite rational, in that they make systematic use of available information, consider the implications of their actions, and thus behave in a sensible manner. Most social behaviour is under volitional control. An individual's action is determined by his/her intention to engage, or not, in a particular behaviour. It's not necessary that intention will always be perfectly correspondent with behaviour. Unless there are unexpected events, people tend to act accordingly with their intentions (Ajzen and Fishbein, 1980).

According to the TRA, an individual's intention is determined by two basic factors. One is the individual's nature, and the other reflects perceived social pressure. The 'individual factor' is "the individual's positive or negative evaluation of performing the behaviour. [Since it deals with personal feelings], this factor is termed the '**attitude towards the behaviour**.'" (Ajzen and Fishbein, 1980, p. 6). The other factor is "the individual's perception of social pressure put on him/her to perform, or not, the behaviour in question. Since it deals with perceived prescription, this factor is termed the '**subjective norm.**'" (Ajzen and Fishbein, 1980, p. 6). In combination, attitude towards the behaviour and subjective norm lead to the formation of a behavioural intention. Generally, people will intend to perform a behaviour when they both have a favourable evaluation of the behaviour and they believe that significant others wish they would do it. In cases where both factors are in correspondence, there is no problem. Clearly, this is not always the case. What will occur where there is conflict? In this situation, the relative importance of the attitude and normative factors need to be taken into account (Ajzen and Fishbein, 1980).

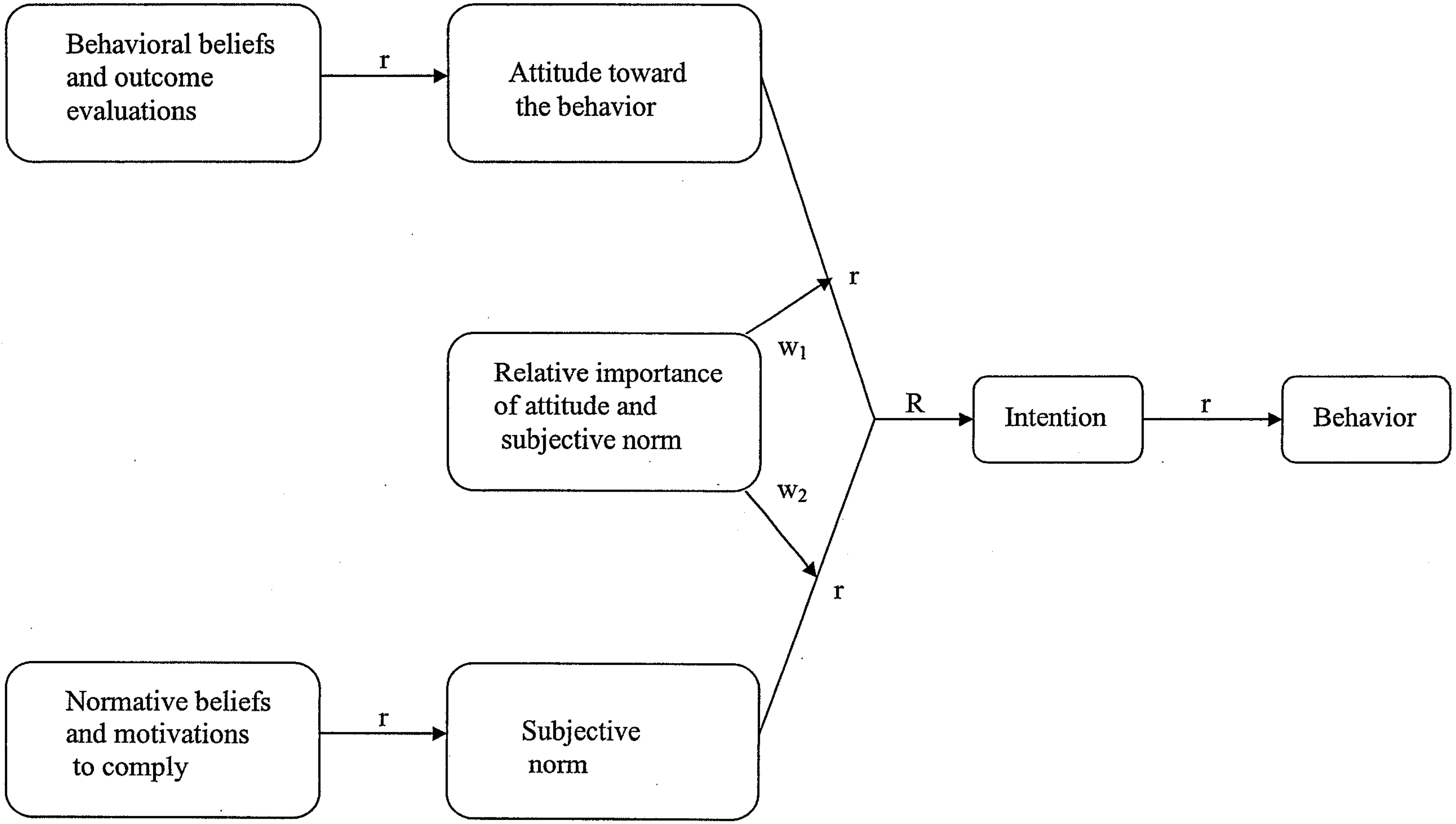
The relative importance of these two factors partly depends on the intention under investigation. For some intentions, attitudinal factors may have stronger influences, while for other intentions normative factors may be more important. Often, both factors become equally significant determinants of intention. Thus, the explanatory value of the theory is greatly enhanced by assigning the relative weights to both determinants. In addition, the individuals' relative weights of both determinants may be different. (Ajzen and Fishbein, 1980).

Intentions represent an individual's motivation in the sense that he/she has a conscious plan, or has made a decision, to exert effort to perform a particular behaviour. Behavioural criteria involve 4 elements: an action, a target, a context, and a time. An action is always performed with respect to a given target, in a given context, at a given point in time. Intentions and behaviour are held to be strongly related when the action, target, context and time frame are assessed at the same level of specificity (a particular action, target, context, and time) or generality (a range of actions, targets, contexts, and times) ( Ajzen, 1988; Ajzen and Fishbein, 1980).

Just as intentions are held to have determinants, so the attitude and subjective norm are also held to have determinants. Attitudes are a function of an individual's salient beliefs. These beliefs are termed '**behavioural beliefs**' and represent perceived outcomes or attributes of the behaviour. The beliefs underlying an individual's subjective norm are termed '**normative beliefs**' and represent the perception of significant others' preferences about whether one should perform the behaviour. The relationships among beliefs, attitude, subjective norm, intention, and behaviour in the TRA are depicted in Figure 4.1.

Although the TRA has been successful in predicting and understanding many behaviours such as weight loss, women's occupational orientations, family planning, consumer behaviour, voting in elections, and changing the behaviour of alcoholics (Ajzen and Fishbein, 1980), it fails to predict behaviour which is not entirely under an individual's (volitional) control. Thus, the TRA restricts itself to volitional behaviours. Behaviour requiring skills, resources, or opportunities not freely available are not considered to be within the domain of the TRA, or are likely to be poorly predicted by the TRA (Fishbein, 1993). Hence, the theory of planned behaviour (TPB) was developed to improve the TRA.

**Figure 4.1** Relationships among beliefs, attitude, subjective norm, intention, and behavior in the Theory of Reason Action (TRA).




**Source:** Ajzen and Fishbein (1980), p. 100.

## 4.3 The Theory of Planned Behaviour (TPB)

In an attempt to strengthen the TRA with regard to behaviours that are not entirely under volitional control, the theory of planned behaviour (TPB) (Ajzen, 1985, 1987, 1988, 1991) was developed. It incorporates perceptions of control over performance of a behaviour (Ajzen, 2002) as an additional predictor. The TPB has become the dominant model in attitude-behaviour literature (Olson and Zanna, 1993), and it has met with some degree of success (Conner and Armitage, 1998).

According to the TPB, people form behavioural intention based on three independent factors. The first two – the attitude towards the behaviour and subjective norm – are the same as in the TRA. The third factor added to the TRA is an individual's perceived control over performance of a behaviour. This factor is termed '**perceived behavioural control,**' and it refers to the perception of ease or difficulty of performing the behaviour. The theory assumes that the attitudes, subjective norms, and perceived behavioural control are the immediate determinants of intentions, and that these behavioural intentions, together with perceived behavioural control are the immediate determinant of behaviour. In addition, the relative importance of intentions and perceived behavioural control may vary across behaviours and situations, as do the relative importance of the three determinants of intentions. (Ajzen, 1985, 1987, 1988, 1991, 2002)

When people have complete control over performing the behaviour, intention alone should be sufficient to predict behaviour. The incorporation of perceived behavioural control should become increasingly useful as perceived control over a performance of behaviour declines. Given a sufficient degree of actual control over the behaviour, people are likely to act in accordance with their intentions. Under specific circumstances, it is only perceived behavioural control and intentions that determine behaviours (Ajzen, 1985, 1987, 1988, 1991, 2002).

Just as the attitude and subjective norm are held to have determinants, so the perceived behavioural control is also held to have determinants. The beliefs underlying an individual's perception of the ease or difficulty of carrying out a behaviour are termed '**control beliefs.**' These factors include both internal control factors (e.g. individual differences, personal deficiencies, information, skills, abilities, will power, emotions and compulsions) and external control factors (e.g. resources, time, opportunities, and dependence on others, obstacles). These were the factors originally offered by Ajzen (1985, 1988) for the concept of perceived behavioural control. However, there were some ambiguities in the concept of perceived behavioural control in its earliest days. There was some overlap between the concepts of perceived behavioural control and Bandura's self-efficacy (people's beliefs about their capabilities of organising and executing the courses of action required to produce given level of attainment (Ajzen, 2002)) (see Manstead and van Eekelen (1998) and Ajzen (2002) for discussion). Ajzen (2002) has clarified the perceived behavioural control concept and proposed that perceived behavioural control comprises two key elements that reflect beliefs about both perceived self-efficacy and perceived controllability, and that this concept can be put into a hierarchical factor model. It is not necessary that self-efficacy and internal control factors correspond, nor controllability and external control factors. Self-efficacy and controllability can reflect internal as well as external factors.

As a general rule, people will have strong intentions to perform a given action if they evaluate it positively, believe that significant others would like them to perform it, and perceive that it is easy to perform. The more favourable the individual's attitude and subjective norm concerning the behaviour, and the greater the individual's perceived behavioural control, the more likely it is that an individual will intend to perform the behaviour (Ajzen, 1985, 1987, 1988, 1991).

The relationships between beliefs, attitude, subjective norm, perceived behavioural control, intention, and behaviour in the TPB is depicted in Figure 4.2. Note that the TPB does not directly deal with the 'actual control' an individual has in a given situation or behaviour. Instead, it takes into account the possible effects of perceived behavioural control on attainment of behavioural goals.

The TPB assumes that perceived behavioural control has motivational implications for intentions. People who believe that they do not have abilities, skills, resources, or opportunities to perform a certain behaviour are unlikely to form strong behavioural intentions to engage in it even if they have favourable attitudes towards the behaviour and believe that significant others wish they would perform it. Thus, an association between perceived behavioural and intention is not mediated by attitude and subjective norm (Ajzen, 1988). This association is represented by the arrow linking perceived behavioural control and intention in Figure 4.2.

In many instances, however, the performance of a behaviour depends not only on intention to do so, but also on a sufficient control over performance of the behaviour under consideration. In this regard, perceived behavioural control can directly influence behaviour (Ajzen, 1988). To the extent that perceptions of behavioural control correspond reasonably well to actual control, perceived behavioural control can serve as a proxy for actual control and contribute to the prediction of the behaviour under consideration (Ajzen, 2002). These associations are represented by the arrow linking perceived behavioural control to behaviour and the arrow linking intention to behaviour in Figure 4.2. Thus, for the behaviour not entirely under volitional control, perceived behavioural control should be added to the prediction of behaviour, over and above the effect of the behavioural intention.

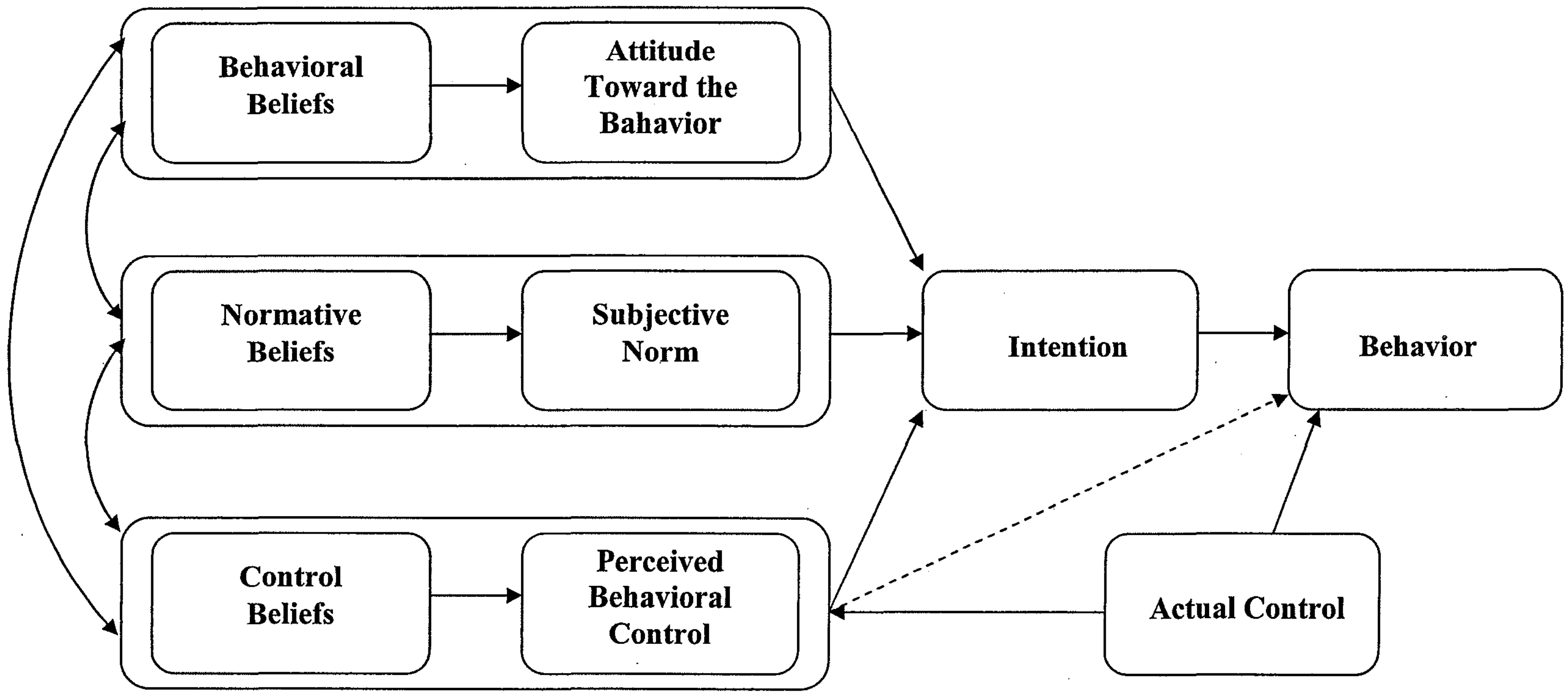
Conner and Armitage (1998) believe

> "The model is held to be a complete theory of behaviour in that influences on behaviour have their impact via the influencing components of the TPB. However, it is perhaps more correctly regarded as a theory of proximal determinants of behaviour. The model gives a description of the process by which attitude and beliefs determine behaviour, but not the processes whereby other variables (e.g. personality) influence components of the TPB."
>
> (Conner and Armitage, 1988, p. 1432).

Indeed, Ajzen (1991) describes his model as open to additional determinants if they significantly contribute to the variance in intention or behaviour:

> "The theory of planned behaviour is, in principle, open to the inclusion of additional predictors if it can show that they capture a significant proportion of the variance in intention or behaviour after the theory's current variables have been taken into account."
>
> (Ajzen, 1991, p. 199).

**Figure 4.2** Relationships between beliefs, attitude, subjective norm, perceived behavioral control, actual control, intention, and behaviour in the Theory of Planned Behavior (TPB).




**Source:** http://www-unix.oit.umass.edu/~aizen/tpb.diag.html (2002)

Since attitudes and personality traits are "typically conceived of as relatively enduring dispositions that exert a pervasive influence on a broad range of behaviours." (Ajzen, 1987, p. 1), and relationships between personality and intelligence have increasingly gained attention from psychologists (Saklofske and Zeidner, 1995; Sternberg and Ruzgis, 1994), all these factors should be considered. It might be useful if personality and intelligence are studied in parallel, to see whether they can make contributions to shared or supplementary variance, when they are used to predict behaviour (Matthews and Deary, 1998). Thus, models of personality traits and theories of intelligence are reviewed to serve as theoretical background to the proposed research in an attempt to explain personal-psychological processes underlying attitude and intention (behavioural plan) of extension agents to the use of an example expert system (POSOP).

## 4.4 Some Models of Personality Traits

Personality traits have been studied since Aristotle's time. There are two traditional assumptions of trait theorists. Firstly, the 'causal primary' of traits. Although Aristotle suggested that causal influence between traits and behaviours might be reciprocal, it is generally believed that the dominant direction of influence is from trait to behaviour. The second assumption is the 'inner locus' of traits. Some important traits, such as extraversion and neuroticism, are assumed by some to relate to genetic factors. Identification and explanation of the sources underlying consistency of behaviour remains the traditional theory (Matthews and Deary, 1998).

Matthews and Deary (1998) gave two concepts of personality traits, in terms of, everyday and scientific conceptions. Firstly, traits are stable over time. It is generally accepted that an individual may behave differently from occasion to occasion, but it is believed that the individual's 'true nature' is defined by a consistent core. Secondly, as with a traditional conception, it is generally assumed that traits directly influence behaviour.

The major task in the scientific psychology of traits is to distinguish the internal properties of a person, and to investigate the causal relationships between traits and behaviour.
For scientific conceptions of personality traits, several distinct steps are necessary. The first step is the measurement and classification of traits, the second step is to test whether,

and how, traits relate to behaviour, and the final stage is the development of satisfactory theory of personality traits. However, there is some question over whether a general scientific theory of traits can be developed (Matthews and Deary, 1998).

There are two kinds of trait approaches; the nomothetic approach, which asserts that people have essentially the same set of traits and differ only in terms of the extent to which they have each trait, and the idiographic approach, which asserts that people differ in terms of which traits they possess – that is some people do not possess traits that others do (Sternberg, 1995). In this study, the nomothetic approach is considered more useful as it provides possible generalised theories, whereas the idiographic approach is fundamentally unique to each individual so that generalised theoretical statements are not possible.

The nomothetic approach includes three popular models, Cattell's (16PF) factors model (Cattell, 1946), the Eysenck's (PEN) widely accepted three-factor model (Eysenck, 1960; 1999), and the Costa and McCrae's (OCEAN) even more widely accepted contemporary five-factor model (Costa and McCrae, 1992b).

### 4.4.1 Cattell' s 16 Personality Factors (16PF) Model

Cattell (1946) started his personality research using the lexicon approach (an approach that seeks for the clusters of the personality descriptors that exist in natural language (Matthews and Deary, 1998)), but later on shifted to questionnaire items. He distinguishes two levels of personality traits: surface traits and source traits. 'Surface traits' are what can be observed as characterising differences among people. 'Source traits' are the underlying psychological dimensions that generate the surface traits. For Cattell, source traits can be found only by factor analysis. Using this technique, the investigator tries to estimate the factors or dimensions that appear to underlie surface variations in behaviour (Sternberg, 1995).

Cattell identified each trait by a letter (or, in some cases, a letter-numeral combination) as well as by a technical term. He invented many of the technical terms he used for designating various source traits. Cattell's last seven traits are called 'Q' traits, for 'questionable,' because he was not as sure of his analysis of these traits as of the other ones. His 23 traits (one of which is an ability trait – Intelligence) are given in Table 4.1 (Sternberg, 1995).

The 16 most robust of these dimensions are measured by the Sixteen Personality Factor Questionnaire (16PF: Cattell, Eber and Tatsuoka, 1970). The 16PF was first developed by Cattell in 1949 as a measure of dimensions that he concluded, through factor analyses of underlying personality data, were basic to human behaviour. As its scales are claimed to represent cultural universals, the 16PF is seemingly suitable for cross-cultural use (Paunonen and Ashton, 1998). In fact, The 16PF "has been extensively used in research and applied settings for more than 40 years. Cattell et al.'s (1970) version of the 16PF became a standard personality measure in research and applied settings for more than 40 years." (Matthews and Deary, 1998, p. 20). "It has, in fact, been translated from English into over 40 different languages (Conn and Rieke, 1994)." (Paunonen and Ashton, 1998, p. 158). These also apply to a Thai context (S. Jamornmarn, personal communication, March 2001).

The 16PF has been criticised for its low internal consistencies on some scales. Furthermore, several investigations using factor analysis of the 16 PF failed to recover the primary factors. Although the 16PF has good predictive validity, the construct validity of its scales remains doubtful, and the linkage between the nature of the constructs and behaviour is obscure (Matthews and Deary, 1998). The latest version of the 16PF, the $16PF_5$ (Cattell, Cattell and Cattell, 1993) has improved its internal consistency, superseding all previous versions. "Of the 185 items in the new edition, 76% were selected as being the best items among all the previous forms of the 16PF, (the wording of over half of those items was then modified); the remaining 24% of the items were completely new" (Paunonen and Ashton, 1998, p. 159).

Paunonen and Ashton (1998) assessed the factor structure of personality inventories in terms of their appropriateness for cross-cultural application. The inventories they evaluated were the California Psychological Inventory (CPI; Gough, 1957, 1987; Gough and Bradley, 1996), the Comrey Personality Scales (CPS;Comrey, 1970, 1995), the 16 Personality Factors Questionnaire (16PF; Cattell, Eber and Tatsuoka, 1970; Cattell, Cattell and Cattell, 1993), the Pavlovian Temperament Survey (PTS; Strelau et al. 1990), the

**Table 4.1** Cattell's 23 traits and their descriptions

| Factor | Low Score Description | High Score Description |
|---|---|---|
| **A** | SIZIA<br>Reserved, detached, critical, aloof | AFFECTIA<br>Warmhearted, outgoing, easy going, participating |
| **B** | LOW INTELLIGENCE[1]<br>Low mental capacity, dull, quitting | HIGH INTELLIGENCE<br>High mental capacity, bright, persevering |
| **C** | LOW EGO STRENGTH<br>Affected by feelings, easily upset, Changeable | HIGH EGO STRENGTH<br>Emotionally stable, face reality, calm |
| **D** | PHLEGMATIC TEMPERAMENT[2]<br>Undemonstrative, deliberate, inactive, stodgy | EXCITABILITY<br>Excitable, impatient, demanding, overactive, unrestrained |
| **E** | SUBMISSIVE<br>Obedient, mild, easily lead, docile, accommodating | DOMINANCE<br>Assertive, aggressive, competitive, stubborn |
| **F** | DESURGENCY<br>Sober, taciturn, serious | SURGENCY<br>Enthusiastic, heedless, happy-go-lucky |
| **G** | LOW SUPEREGO STRENGTH<br>Disregards rules and group moral standards, expedient | HIGH SUPEREGO STRENGTH<br>Conscientious, persistent, moralistic, staid |
| **H** | THRECTIA<br>Shy, timid, restrained, threat-sensitive | PARMIA<br>Adventurous, 'thick-skinned,' socially bold |
| **I** | HARRIA<br>Tough-minded, rejects illusions | PREMSIA<br>Tender-minded, sensitive, dependent, overprotected |
| **J** | ZEPPIA[2]<br>Zestful, liking group action | COASTHENIA<br>Circumspect individualism, reflective, internally restrained |
| **K** | SOCIAL UNCONCERN[2]<br>Socially untutored, unconcerned, boorish | SOCIAL-ROLE CONCERN<br>Socially mature, alert, self-disciplined |
| **L** | ALAXIA<br>Trusting, accepting conditions | PROTENSION<br>Suspecting, jealous, dogmatic |

[1] Factor B (INTELLIGENCE) is an ability trait rather than a temperament trait.

[2] One of the 'seven missing factors,' so termed because they were not identified by the original 16PF.

**Table 4.1** Cattell's 23 traits and their descriptions (cont.)

| | | |
|---|---|---|
| **M** | PRAXERNIA<br>Practical, has 'down-to-earth' concerns | AUTIA<br>Imaginative, bohemian, absent-minded |
| **N** | NAIVETE<br>Forthright, unpretentious | SHREWDNESS<br>Astute, worldly, polished, socially aware |
| **O** | UNTROUBLED ADEQUACY<br>Self-assured, placid, secure, complacent | GUILT PRONENESS<br>Apprehensive, self-reproaching, insecure, troubled |
| **P** | CAUTIOUS INACTIVITY[2]<br>Melancholy, cautious, takes no risks | SANGUINE CASUALNESS<br>Sanguine, speculative, independent |
| **$Q_1$** | CONSERVATISM<br>Disinclined to change, respects traditional values | RADICALISM<br>Experimenting, analytic, free thinking |
| **$Q_2$** | GROUP DEPENDENCY<br>A 'joiner,' sound flower | SELF-SUFFICIENCY<br>Self-sufficient, resourceful, prefers own decisions |
| **$Q_3$** | LOW SELF-SENTIMENT<br>Uncontrolled, lax, follows own urges | HIGH-SELF SENTIMENT<br>Controlled, exacting willpower, socially precise, compulsive, follows self-image |
| **Q4** | LOW ERGIC TENSION<br>Relaxed, tranquil, unfrustrated, composed | HIGH ERGIC TENSION<br>Tense, frustrated, driven, overwrought, fretful |
| **$Q_5$** | LACK OF SOCIAL CONCERN[2]<br>Does not volunteer for social service, experiences no obligation, self sufficient | GROUP DEDICATION WITH SENSED INADEQUACY<br>Concerned with social good works, not doing enough, joins in social endeavours |
| **$Q_6$** | SELF-EFFACEMENT[2]<br>Quiet, self-effacing | SOCIAL PANACHE<br>Feels unfairly treated by society, self expressive, makes abrupt antisocial remarks |
| **$Q_7$** | LACKS EXPLICIT SELF-EXPRESSION<br>Is not garrulous in conversation | EXPLICIT SELF-EXPRESSION<br>Enjoys verbal-social expression, likes dramatic entertainment, follow fashionable ideas |

[1] Factor B (INTELLIGENCE) is an ability trait rather than a temperament trait.

[2] One of the 'seven missing factors,' so termed because they were not identified by the original 16PF.

**Source:** Sternberg (1995), p. 624-25

Personality Research Form (PRF; Jackson, 1984), and the Nonverbal Personality Inventories (NPQ:Paunonen, Jackson and Keinonen, 1990). They concluded that the16PF$_5$ (Cattell, Cattell and Cattell, 1993) gave a high degree of cross-cultural stability to the factor structure.

### 4.4.2 Eysenck's Three-Factor (PEN) Model

According to Eysenck's three-factor (PEN) model, there are three broad personality factors: Psychoticism (P), Neuroticism (N), and Extraversion-Introversion (E). The three traits and definitions are given in Table 4.2. These factors are assessed using a self-report questionnaire in which the test taker is required to answer 'yes', 'no', or 'can't decide' to a number of questions. The questionnaire has evolved through several different versions, culminating in the Eysenck Personality Questionnaire-Revised (EPQ-R) (Eysenck and Eysenck, 1991), the Eysenck Personality Profiler (EPP) (Eysenck and Wilson, 1991; 1999), and the Eysenck Personality Profile (Short) (EPP-S) (Eysenck, Wilson and Jackson, 1996; 1999) (Jackson et al., 2000).

As with the 16PF, the EPQ has been translated into many different languages and tested for cross-cultural validity of the PEN model. Cross-cultural research was studied in 13 countries, including Greece, France, Australia, Yugoslavia, Sicily, Spain, Hungary, and non-Western countries such as Bangladesh, Brazil, Hong Kong, India, Japan, and Nigeria, using carefully translated versions of the Eysenck Personality Questionnaire (EPQ; Eysenck and Eysenck, 1975). In each case, the same dimensions of personality traits as the British samples were evidenced, not only in the European cultural groups, but also in other nationalities. In general, the same four factors P, E, N and L (lie scale) were extracted from each data set, showing a high level of cross-cultural generalisability. Psychoticism (P) indices of factor comparisons seemed to have low values in some countries, especially none-Western ones such as female samples in Nigeria and male samples in Japan (Eysenck and Eyseck, 1982). Similar results have been obtained in subsequent studies, when using the revised EPQ (EPQ-R; Eysenck, Eysenck, and Barrett,1985) (Matthews and Deary, 1998).

**Table 4.2** Definitions of the primary scales of the Eysenck Personality Profiler (EPP).

| Superfactor | Primary scale | Description – High scorers are... |
|---|---|---|
| **Psychoticism (P)** | **P1: Risk-taking** | Reward-seeking and like to live dangerously with little concern for the possible adverse consequences. |
| | **P2: Impulsiveness** | inclined to act on the spur of the moment, make hurried, often premature decisions and are usually carefree, changeable and unpredictable. |
| | **P3: Irresponsibility** | inclined to be overly casual, thoughtless, careless of protocol, unpredictable and socially unreliable. |
| | **P4: Manipulativeness** | detached, calculating, shrewd, worldly, expedient and self-interested in their dealings with other people. |
| | **P5: Sensation-seeking** | forever seeking thrills in life and have an insatiable thirst for novel experiences. |
| | **P6: Tough-mindedness** | tolerant of and probably enjoy violence, obscenity and swearing. |
| | **P7: Practical** | inclined to be practical, are interested in doing things rather than thinking about them and tend to be impatient with ivory tower theorising. |
| **Extraversion** | **E1: Activity** | generally active, energetic, starters of work and proactive. |
| | **E2: Sociability** | inclined to seek out the company of other people and are generally happy and comfortable in social situations. |
| | **E3: Assertiveness** | Independent, dominant and stand up for their rights, perhaps to the extent of being viewed as 'pushy'. |
| | **E4: Expressiveness** | open with their feelings, volatile and demonstrative |
| | **E5: Ambition** | ambitious, hard-working, competitive, keen to improve their social standing and place a high value on productivity. |
| | **E6: Dogmatic** | uncompromising in their views on most matters and they are likely to defend them vigorously and vociferously. |

**Table 4.2** Definitions of the primary scales of the Eysenck Personality Profiler (EPP) (cont.).

| Superfactor | Primary scale | Description – High scorers are... |
|---|---|---|
| | **E7: Aggression** | given to the direct or indirect expression of aggression through temper tantrums, fighting, violent argument and sarcasm. |
| **Neuroticism** | **N1: Inferiority** | Low in self-esteem, have a low opinion of themselves and believe themselves to be failures. |
| | **N2: Unhappiness** | characteristically pessimistic, gloomy and depressed, disappointed with their existence and at odds with the world. |
| | **N3: Anxiety** | easily upset by things that go wrong and are inclined to worry unnecessarily about unpleasant things that may or may not happen. |
| | **N4: Independence** | lacking in self-reliance, think of themselves as helpless pawns of fate, are pushed around by other people and events and show a high degree of what has been called 'authoritarian submission' the unquestioning obedience to institutional power. |
| | **N5: Hypochondria** | likely to acquire psychosomatic symptoms and imagine that they are ill. |
| | **N6: Guilt** | Self-blaming, self-abasing and troubled by their conscience regardless of whether their behaviour is really morally reprehensible. |
| | **N7: Obsessiveness** | careful, conscientious, highly disciplined, staid, finicky and easily irritated by things that are unclean, untidy or out of place. |
| | **L: Lie scale** | Able to put themselves in a positive light so as to try and create a positive impression. |

**Source**: Jackson et al. (2000), p.237-39

Criticism of the EPP (Jackson et al., 2000) includes noting that some scales have a relatively low internal consistency, there seem to be too many neuroticism scales, and the three category response scales seem inadequate. EPP is only the EPQ that attempts to measure traits at both the primary factor and super-factor level.

### 4.4.3 Costa and McCrae's Five-Factor (OCEAN) Model

The http://www.ipat.com/bigfive.html (2003, p. 1) website states that

> "In the1960s Cattell derived five broad factors from analysis of his 16 Primary scales. These global scales have been called "the original Big Five" because they preceded the models [that are] popular today. For example, Costa and McCrae factor analysed 16PF data in the development of their five-factor model...his [Cattell's] five-factor model is very similar to Goldberg's Big Five and Costa and McCrae's [OCEAN] five-factor model."

Comparisons of these five-factor models and Eysenck's three-factor (PEN) model are given in Table 4.3.

**Table 4.3** Comparisons of the traits in five-factor models and Eysenck's three-factor model.

<table>
<tr><th>Costa and McCrae' s OCEAN</th><th>Catell' s Big Five</th><th>Goldberg' s Big Five</th><th>Eysenck' s PEN model</th></tr>
<tr><td>Extraversion</td><td>Introversoin/ Extraversion</td><td>Surgency</td><td>Extraversion</td></tr>
<tr><td>Neuroticism</td><td>Low Anxiety/ High Anxiety</td><td>Emotional Stability</td><td>Neuroticism</td></tr>
<tr><td>Openness</td><td>Tough-Mindedness/ Receptivity</td><td>Intellect</td><td></td></tr>
<tr><td>Agreeableness</td><td>Independence/ Accommodation</td><td>Agreeableness</td><td rowspan="2">Psychoticism (reverse scales.)</td></tr>
<tr><td>Conscientiousness</td><td>Low Self-Control/ High Self-Control</td><td>Conscientiousness</td></tr>
</table>

**Source**: Adapted from http://www.ipat.com/bigfive.html (2003).

The development of the Costa and McCrae's OCEAN model has been driven by a mixture of rational and statistical concerns. From a wide range of personality research results they decided the domains to be measured, and then constructed scales to assess them, which were then subjected to factor analysis (Matthews and Deary, 1998).

According to Costa and McCrae's OCEAN model, there are five broad dimensions: Openness (O), Conscientiousness (C), Extraversion (E), Agreeableness (A), and Neuroticism (N). These dimensions are assessed by the NEO-Personality Inventory - Revised (NEO-PI-R), or the NEO-Five Factor Inventory (NEO-FFI) (Form S of the NEO-PI-R) (Costa and McCrae, 1992b).

The NEO-PI-R is made up of 240 questions, 48 for each of the five dimensions or 'domains.' The response to each question is made on a five-point scale from 'strongly agree' to 'strongly disagree.' Each dimension is composed of six facets – lower-level traits – each of which is assessed by eight questions (3 validity items are also included). The facets that make up of each these broad domains are given in Table 4.4.

The NEO-FFI is made up of 60 questions, 12 for each of the five domains. It provides a brief, comprehensive measure of the five domains. Information on specific facets within each domain is not provided, and the shorter scales are somewhat less reliable and valid than the full NEO PI-R.

Gerbing and Tuley (1991) examined the relationship between the NEO-PI (Costa and McCrae, 1985) and the 16PF (Cattell, Eber and Tatsuoka, 1970). They found that both inventories measured approximately the same aspects of personality and noted that similarities between the NEO-PI and 16PF tended to be obscured by the differences in the words used in naming factors, and in identifying the level at which the factors are defined. As they put it, "The five NEO-PI factors correspond to second-order factors on the 16PF, and the 18 NEO-PI factor facets correspond to the 16PF first-order factors." (Gerbing and Tuley, 1991, p. 286). The NEO-PI corresponds to the 16PF for all scales, except for Shrewdness and Intelligence, with particularly strong relationships between Extraversion (E) and Neuroticism (N) across the two inventories. They concluded that:

**Table 4.4** Trait facets associated with the five domains of the Costa and McCrae's Five-Factor (OCEAN) Model.

| Domains | Facets |
|---|---|
| **Openness (O)** | O1: Fantasy<br>O2: Aesthetics<br>O3: Feelings<br>O4: Actions<br>O5: Ideas<br>O6: Values |
| **Conscientiousness (C)** | C1: Competence<br>C2: Order<br>C3: Dutifulness<br>C4: Achievement Striving<br>C5: Self-Discipline<br>C6: Deliberation |
| **Extraversion (E)** | E1: Warmth<br>E2: Gregariousness<br>E3: Assertiveness<br>E4: Activity<br>E5: Excitement-seeking<br>E6: Positive Emotions |
| **Agreeableness (A)** | A1: Trust<br>A2: Straightforwardness<br>A3: Altruism<br>A4: Compliance<br>A5: Modesty<br>A6: Tender-Mindedness |
| **Neuroticism (N)** | N1: Anxiety<br>N2: Angry Hostility<br>N3: Depression<br>N4: Self-Consciousness<br>N5: Impulsiveness<br>N6: Vulnerability |

**Source**: Costa and McCrae (1992b)

> "This research supports to some extent Costa and McCrae's (1977) conclusion that the 16PF is weakest in terms of Openness, but Scales I, M, and Q1 do provide a representation of the 16PF for the Openness domains, as first noted by Costa and McCrae (1976, 1977) based on their cluster analysis of 16 PF scale scores. Moreover, NEO-PI Conscientiousness corresponds to Scale G, and NEO-PI Agreeableness corresponds somewhat to Scale L."
>
> (Gerbing and Tuley, 1991, pp. 286-87).

The NEO-PI does provide a measure of the five domains. However, the 16PF provides a measure of 'Intelligence,' a domain not at all addressed by the NEO-PI. (Gerbing and Tuley, 1991). Openness (O) is particularly related to divergent thinking that contributes to creativity (McCrae, 1987), and it is slightly associated with both education and measured intelligence (Costa and McCrae, 1992b). However, Costa and McCrae (1992b) argued that:

> "Openness (O) is by no means equivalent to intelligence. Some very intelligent people are closed to experience, and some very open people are quite limited in intellectual capacity. In a factor analytic sense, measures of cognitive ability form a sixth, independent factor that we regard as being outside the domain of personality proper."
>
> (Costa and McCrae, 1992b, p. 15).

McCrae and Costa (1997) assessed the cross-cultural generalisability of their OCEAN model using the NEO-PI-R (Costa and McCrae, 1992b) in 6 countries; Germany, Portugal, Israel, China, Korea, and Japan. The results showed remarkable similarities in the factor structure of the NEO-PI-R across cultures and languages, particularly when targeted rotations were used. Because of the rich language and cultural diversity of the samples studied, the authors claimed that personality trait structure is universal. They also sought to convince others that there was considerable agreement among many seemingly different personality schemes by correlating their scales with those from many other well-known personality instruments. In fact, Costa and McCrae (1995) correlated the revised EPP (Eysenck and Eysenck, 1991) scales with the revised NEO-PI (NEO-PI-R; Costa and McCrae, 1992b) facet scales. In general, the correlations provided strong support for the convergent and discriminant validity of the EPP scales, suggesting that the EPP scales measure the constructs they are intended to do. However, varimax and targeted validimax factor analyses suggested some EPP scales were not correctly grouped into higher order factors, and that a five-factor model seemed more appropriate for the EPP than the three-factor model. On the other hand, Jackson et al. (2000) investigated possible three- and five-factor solutions to the EPP (Eysenck et al., 1992) using exploratory factor analysis, by means of structural equation modelling, to estimate the goodness-of-fit of three- and five-factor models. Neither a three- nor a five- factor solution was satisfactory confirmed, and insufficient evidence was found to support the suggestion made by Costa and McCrae (1995).

Costa and McCrae (1992a) gave the evidence for the validity of the Five Factor Model by summarising the four ways on which the five factors are based: (1) the five robust factors are found in both longitudinal and cross-sectional studies; (2) the traits based on the five factors are derived from studies of different personality systems and of natural language; (3) a wide range of age, race, and language groups have shown the five factors underlying behavioural dispositions; and (4) each of the five factor is based on genetic factors and is heritable.

Criticisms of the five-factor model have focused on three issues. Firstly, the five factors obtained by different investigators (e.g. Goldberg's (1990) Big Five) are not necessarily equivalent although many psychologists refer to the Big Five and the five-factor model interchangeably. Costa and McCrae's OCEAN model is based on factor analyses of questionnaires. It is hierarchical, in that the five factors are obtained through factor analyses of lower-order facets, whereas Goldberg' s Big Five are derived from factor analyses of adjectives and are not hierarchical, but circular (http://www.personality research.org/bigfive.html, 2003). "Comparative studies of different Big Five measures indicate that they are not completely interchangeable. For example, Golberg (1992) correlated lexically defined factors with the NEO-PI scales, and obtained correlations between supposedly equivalent measures ranging from 0.46 to 0.69.... The lowest correlation of 0.46 here was between lexical and questionnaire measures of Openness" (Matthews and Deary, 1998, p. 32). Openness (O) has been the most difficult factor to define precisely. It has been termed intellect, culture or imagination in lexical systems (Digman and Takemoto-Chock, 1981).

Secondly, some researchers believe five broad trait factors may be insufficient, others believe five factors may be too many, and still others that five factors may be just about right. Some criticised the five factor solutions as being much too simple to summarise everything that is known about individual differences in personality (e.g. Cattell, 1993).

Furthermore, there may be some factors hidden in the residual of the factor solutions. Some studies suggested the existence of a sixth factor, 'culture' (Digman and Takamoto-Chock, 1981), or intelligence (Krung and John, 1986). Eysenck (1967) criticised all five factors are not necessary, indeed, the five-factor model was preceded by a widely accepted three-factor model. Eysenck (1991) argued that agreeableness (A) and conscientiousness (C) are primary level traits that are both facets of his higher-order Psychoticism (P). In general, these studies lack what the five-factor model has attained, a model that can be replicated across contexts, subjects, and modes of measurement. Five factors seem just about right (Moberg, 1999).

Thirdly, some criticised the five-factor model as being atheoretical. According to Block (1995), it is not based on personality theory. He believes it is based on words used by non-professionals in judging themselves (through questionnaires), and others (through ratings). This raises the possibility that the five-factor model is nothing more than a reflection of ordinary people's cognitive biases (Digman, 1990). According to Moberg (1999), the reliance on factor analysis worsens this problem as much is left to the interpretation as the data speaks for itself regardless of conceptual developments.

In conclusion, trait theorists often disagree about the specific contents and structure of the basic traits needed to describe personality, but their general conceptions have much in common and they remain popular (Deary and Matthews, 1993). They all use the 'trait' to account for consistencies in an individual's behaviour and to explain why people respond differently to the same stimulus. Most view traits as dispositions that determine such behaviours. Each trait differentiates between relatively superficial traits (e.g. Cattell's surface traits, Eysenck's superfactors, Costa and McCrae's domains), and more basic underlying traits (e.g. Cattell's source traits, Eysenck's primary scales, Costa and McCrae's facet scales). Each researcher recognised that traits vary in breadth or generality, and each has searched for relatively broad, stable traits. Their main emphasis in the study of personality is the development of instruments that can accurately tap the person's underlying traits.

### 4.5 The Triarchic Theory of Intelligence

While some psychologists regard intelligence as part of personality, most believe it is a separate factor. Thus, it is important to review ideas on intelligence and how it might be measured. As cited in Sternberg (1995), intelligence has been studied since 1883. Two early workers were Francis Galton (1883) who emphasised psychophysical acuity, and Alfred Binet (1916) who emphasised judgement.

Intelligence is hard to define and describe in a single definition (Gregory, 1996). The term 'intelligence' is used in different ways by many with different points of view (Sternberg and Salter, 1982). There is no universally accepted definition for intelligence among educators and psychologists. Two early definitions of intelligence are Baldwin's (1905) and Thorndike's (1962). Baldwin defines "intelligence (or intellect) as the faculty or capacity of knowing (Baldwin, 1905)." (Butterworth, 1996, p. 50), whereas Thorndike (1962) believed it was "the ability to learn" (Campione, Brown, and Ferrara, 1982, p. 437). Both Baldwin and Thorndike view intelligence as a unitary trait of human ability.

Not until 1921, in a symposium on 'Intelligence and its Measurements' was intelligence defined as "the capacity to learn from experience and the ability to adapt to the surrounding environment." (Sternberg, 1995, pp. 381-2). There are two important implications in these common themes. Firstly, capacity to learn from experience suggests, that smart people do not keep making the same mistakes again and again; rather, they learn from their mistakes. Secondly, adaptation to the environment implies how people lead their life in general e.g. handle a job, get along with other people, etc. (Sternberg, 1995). In a Handbook of Human Intelligence, intelligence is defined as "goal-directed adaptive behavior." (Sternberg and Salter, 1982, p. 3). Again, it implies two intelligent behaviours – goal-directed and adaptive. This emphasises that intelligent behaviour must not only be adaptive, but also be goal-directed. Aimless behaviour would not count as intelligent behaviour though it's adaptive. (Sternberg and Salter, 1982). However, contemporary psychologists stress the importance of '**metacognition**' – how people understand and control their own thinking and reasoning process while they solve problems and make decisions. They also stress the importance of '**culture**,' – behaviour regarded as intelligence in one culture may be regarded as stupid in another (Sternberg, 1995).

The view of intelligence as a unitary trait of human ability has now been replaced by contemporary psychologists, Gardner and Sternberg. Gardner (1983, 1993) views intelligence as multiple abilities. He defines "intelligence" as a group of abilities that is somewhat autonomous from other human capacities, has a core set of information-processing operations, has a distinct history in the stages of development individuals pass through, and has plausible roots in evolutionary history. His seven aspects of intelligence are:

(1) Verbal-Linguistic - The ability to use words and language.

(2) Logical-Mathematical - The capacity for inductive and deductive thinking and reasoning, as well as the use of numbers and the recognition of abstract patterns.

(3) Visual-Spatial - The ability to visualise objects and spatial dimensions, and create internal images and pictures.

(4) Bodily-Kinesthetic - The wisdom of the body and the ability to control physical motion.

(5) Musical-Rhythmic - The ability to recognise tonal patterns and sounds, as well as a sensitivity to rhythms and beats.

(6) Interpersonal - The capacity for person-to-person communications and relationships.

(7) Intrapersonal - The spiritual, inner states of being, self-reflection, and awareness.

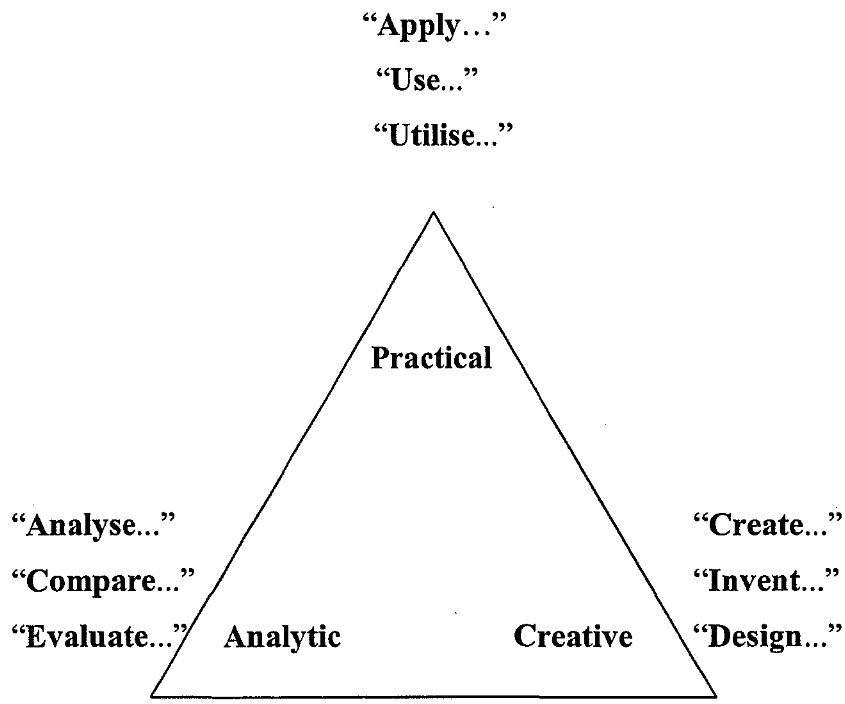
He claimed that these multiple intelligence aspects are separate and somewhat independent, based partly on evidence from patients who suffer certain brain damage which often disrupts one aspect of intelligence, but not the others (Gardner, 1993).

Gardner (1983, 1993) stresses the separateness of the multiple intelligence aspects. On the other hand, Sternberg (Sternberg, 1985, 1988, 1995) emphasises that they work together in his Triarchic Theory of Human Intelligence. However, both Gardner and Sternberg stress information processing as an important operation of intelligence (Sternberg, 1995).

According to Sternberg's Triarchic Theory of Human Intelligence,

> "intelligence comprises analytic, creative, and practical abilities. In analytical thinking, we try to solve familiar problems by using strategies that manipulate the elements of a problem or the relationships among the elements (e.g., comparing, analyzing). Increative thinking, we try to solve new kinds of problems that require us to think about the problem and its elements in a new way (e.g., inventing, designing). In practical thinking, we try to solve the problems that apply what we know to everyday contexts (e.g., applying, using)."
>
> (Sternberg, 1995, p. 395).

**Figure 4.3** Sternberg's Triarchic Theory of Intelligence




**Source:** Sternberg (1995), p. 395

These abilities deal with the relationships of intelligence to an individual's internal world, or himself/herself; experience or reaction between the internal and external worlds, or an individual and his/her surrounding environment; and the external world, or an individual's surrounding environment (Sternberg, 1988).

In regard to the relationship of intelligence to an individual's internal world, the theory stresses three types of highly interdependent components used for processing information. These are:

> "(1) metacomponents – executive processes (i.e., metacognition) used to plan, monitor, and evaluate problem solving; (2) performance components – lower order processes used for implementing the commands of the metacomponents; (3) Knowledge-acquisition components – the processes used for learning how to solve the problems in the first place."
>
> (Sternberg, 1995, p. 395).

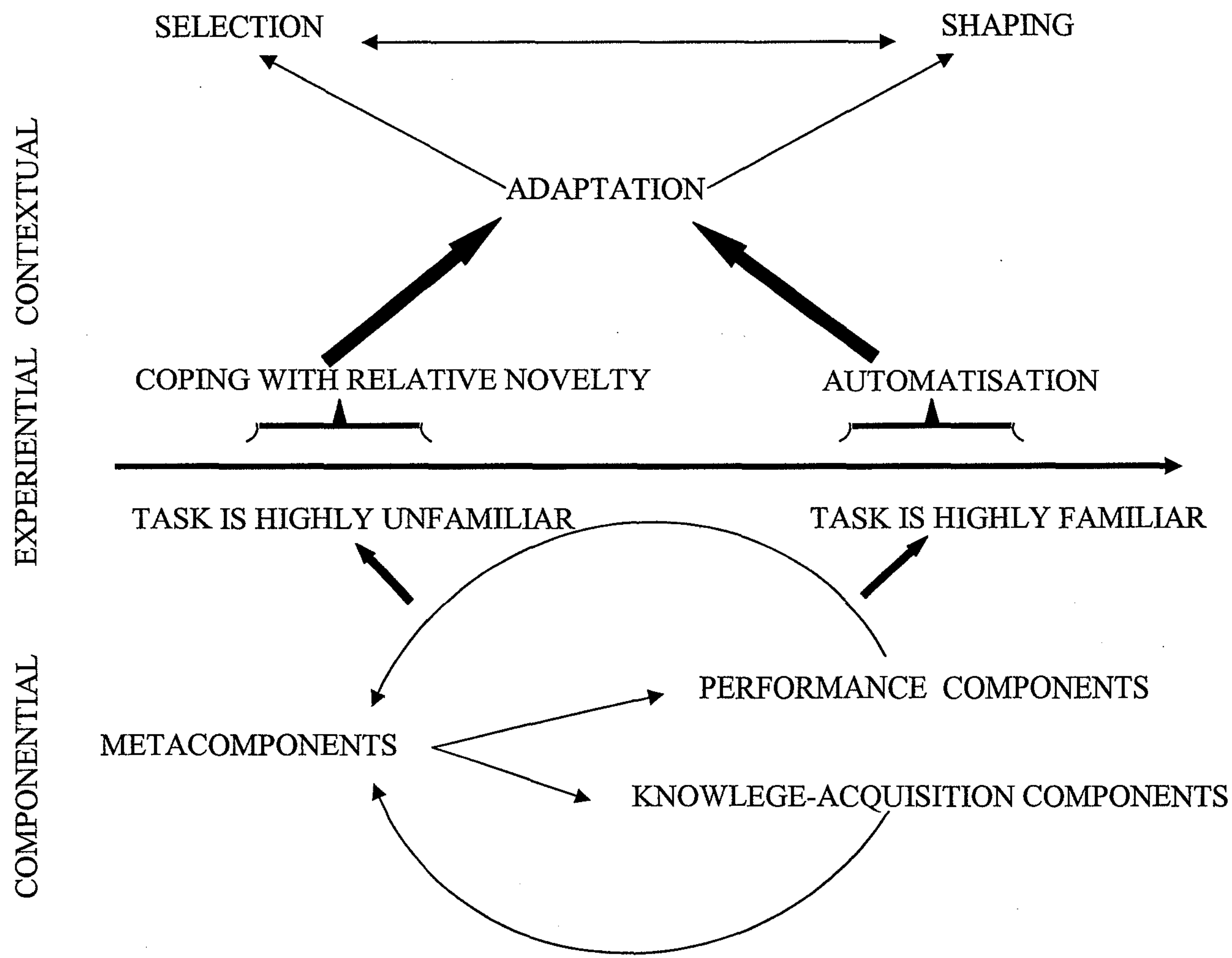
The theory also considers the relationship of intelligence to an individual's experience, or the reaction between the three types of information-processing components and prior experience. An individual faces tasks and situations with which he/she has different levels of experience, ranging from completely new to him/her to completely familiar with him/her. In other words, he/she has no prior experience to extensive experience. Once a task has become increasingly familiar, it requires less conscious effort for deciding what to do next and how to do it as many steps of the task may become automatic. A novel task requires more intelligence than that of "a task for which automatic procedures have been developed" (Sternberg, 1995, p. 396).

The relationship of intelligence to an individual's external world is also important. The theory also proposed that intelligence in everyday life is purposive with regard to an individual life and abilities. The three types of components of intelligence are applied to experience in order to serve three functions in the real-world contexts: adaptation to existing environments, shaping of existing environments into new environments, and selection of new environments. Generally, one would try to adapt first, if that fails, or is unsatisfactory, the person would try to shape the environments or select new environments (Sternberg, 1988).

The relationships among the various aspects of the Triarchic Theory of Human Intelligence are depicted in Figure 4.4. According to the Triarchic theory, intelligence is applied to a wide-range of problems, and it varies from one individual to another. For instance, one may be clever at solving abstract or academic problems, while another may be clever at solving concrete or practical problems. An intelligent individual is not defined as someone who is excellent in all aspects of intelligence; rather, an intelligent person knows his/her own strengths and weakness. He/she makes the most of his/her strengths, either compensates for, or remedies, his/her weakness (Sternberg, 1995).

Sternberg has developed the Sternberg Triarchic Abilities Test (STAT), which yields separate scores for each ability that corresponds to each aspect of intelligence proposed by

**Figure 4.4** Relationships among the various aspects of the Triarchic Theory of Human Intelligence




**Source:** Sternberg (1988), p. 68.

his Triarchic Theory (http://www.newhorizons.org/future/Creating_the_Future/crfut_sternberg.html, 2003). However, there is limited use of STAT. This is discussed in the research design and methods chapter.

## 4.6 Conceptual Framework

Expert systems have been identified as a decision support tool with extensive potential in developing countries as a cost-effective means of extension program delivery (Gum and Bank, 1990), particularly when supported by generalist extension agents as in Thailand. They have the potential to increase each extension agents' expertise and provide assistance in solving integrated management problems. Knowledge-based expert systems provide opportunities to increase the production management knowledge of all extension agents, regardless of background and training (Sullivan and Ooms, 1990). Despite this potential (Rafea, 1998), however, it is not known, particularly for Thailand whether expert systems will be accepted by extension agents, and provide real value. There may be several factors, both the systems themselves and the extension agents' characteristics, influencing the acceptance of the systems. Clearly, the confidence of the extension agents in the systems' ability to provide accurate and reliable advice, and other resource and technical support are crucially important to the adoption or rejection of the systems. Furthermore, the extension agents' attitudes towards the features of the systems, and thus use of the systems as decision support tools, their personal characteristics, such as personality traits, as well as intelligence, might all be equally important to the adoption or rejection of the systems.

In this study, an example expert system for rice disease diagnosis and management (POSOP) was used in investigating effects of extension agents' attitudes towards its features on their attitudes towards using it as a decision support tool. As POSOP is intended to be a decision support tool for the agents, its value as a support tool as perceived by the agents, and the success of its user interface, were studied as these two features are analogous to human experts and their communication with clients.

The proposed theory and operational model are based on the theory of planned behaviour (TPB) (Ajzen, 1985, 1987, 1988, 1991; http:www-unix.oit.umass.edu/~aizen/tpb/diag.html, 2002). The TPB is chosen as it is widely accepted, tightly specified, and open to the inclusion of the additional variables.

The model assumes that extension agents are rational and make systemic use of information available to them, they consider the implication of using POSOP before deciding to use, or not to use it, but the use of POSOP is not entirely under their volitional control.

The use of POSOP is determined by the agents' intention, which refers to the motivational factors that influence POSOP's use. It indicates how hard they are willing to try, and how much of an effort they are planning to attempt in using POSOP. Their intention, in turn, is determined by the relative importance of three independent determinants: the first, which is a personal factor, is their attitude towards using it in the sense of the degree to which the agents have a favourable, or unfavourable, evaluation of using POSOP. The second, which is a social factor, is their subjective norm. This refers to the perceived social pressure to use, or not to, use POSOP. The third is the degree of perceived behavioural control. This refers to their perception of difficulty, or ease, of using POSOP.

As a general rule, the stronger the agents' intention to use POSOP, the more likely they will use it. The more favourable their attitude and their subjective norm with respect to using POSOP, and the greater their perceived behavioural control, the stronger should be their intention to use POSOP.

This study attempts not only to predict, but also to explain the potential behaviour of the extension agents. The agents' behaviour is explained once its determinants have been traced to the beliefs that underlie their attitude and subjective norm with regard to using POSOP, and also their perceived control over using it. Generally speaking, a person forms her/his beliefs from her/his past experience; exposure to different kinds of information, be it incomplete or incorrect, leads to the formation of different beliefs (Fishbein and Ajzen, 1975). "Personality variables and traditional attitudes are sometimes viewed as residues of past experience, or are assumed to influence the person's interpretation of his environment and thus the beliefs he holds." (Ajzen and Fishbein, 1980, p. 91).

The beliefs underlying the agents' attitude towards the use of POSOP are termed 'behavioural beliefs' and represent their beliefs about using POSOP and the likely outcomes; the beliefs underlying their subjective norm are termed 'normative beliefs' and represent their perception of significant others' preferences about whether they should use

POSOP, and their motivation to comply with their significant others; and the beliefs underlying their perceived behavioural control are termed 'control beliefs' and represent the beliefs on their own knowledge and skills in, and the facilities available for, using POSOP.

Attitudes and personality traits are "typically conceived of as relatively enduring dispositions that exert a pervasive influence on a broad range of behaviours (Ajzen, 1987, p. 1). In the domain of social psychology the attitude concept has focussed on explanations of consistency of human behaviour. Social psychologists attempted to collect descriptive data regarding attitudes towards various social issues and considered questions of consistency among cognitive (opinion, beliefs), affective (feelings, evaluations), and conative (behavioural intentions) components of attitudes (Ajzen, 1987, 1988; Fishbein and Ajzen, 1975). Similarly, in the domain of personality psychology the trait concept has focussed attention on explanations of the stable underlying dispositions. Personality psychologists have devoted a considerable effort to determine the personality structures in terms of multidimensional trait configuration (Cattell, 1946; Costa and McCrae, 1992b; Eysenck, 1960, 1999).

Ajzen and Fishbein (1980) noted that whatever the behaviour, one or more personality traits appear to underlie or influence any behaviour in question. However, traditional attitudes towards target objects (people, institutions, and policies), personality traits, and intelligence are likely to be indirectly related to the behaviour. In other words, it is suggested that variables external to the TPB influence the behaviour via its determinants, or more specifically, as they put it,

> "effects of external variables are mediated by beliefs, and therefore, taking the external variables into account (in addition to beliefs) is not expected to improve prediction of attitudes or subjective norms. For the same reason, measuring external variables in addition to a person' s attitudes and subjective norm is not expected to improve the prediction of intentions, nor should measuring them in addition to intentions improve prediction of behaviour."
>
> Ajzen and Fishbein (1980, p. 91)

Since the behaviour (actual use of POSOP) could not be measured in this study, the relationships between perceived behavioural control and intention, and the resultant behaviour could not be explored. Thus, the study focused on the contributions of attitude, subjective norm, and perceived behavioural control, and their determinants, plus the variables external to the TPB, to the prediction and explanation of intention. It is assumed, therefore, that behaviour will be correlated with intention. Measuring the actual behaviour will have to wait until several years have passed.

The OCEAN model of personality traits (Costa and McCrae, 1992b) was used in the model as the five domains (Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism) as discussed previously, are widely accepted and claimed to represent a universal structure for personality (McCrae and Costa, 1997). In addition, the OCEAN model has been tested in a wide range of cultures (Moberg, 1999). Unfortunately, its evidence in Thai culture has not been reported although both of its measuring instruments (NEO-PI-R and NEO-FFI) have been translated into two Thai versions by Smithikrai, and by Chittcharat and Suraksa (N. Chittcharat, personal communication, 10 January 2002). The version by Chittcharat and Suraksa has been verified and approved by Costa and McCrae (N. Chittcharat, personal communication, 10 January 2002).

This study hypothesises that the extraverted agents may not be interested in using POSOP as they are sociable and like talking to people and therefore may obtain information for their decision support from other people. On the other hand, the introverted agents might be interested in using the system as they are reserved, and may relate more comfortably to a machine as a source of information for their decision support work. Use of POSOP as a decision support tool for rice disease diagnosis and management is regarded as a new experience to extension agents in Thailand, and therefore, extension agents with an 'open' personality might be interested in using POSOP more than 'closed' ones as their nature is open to new experience. Hence, only the two personality domains of interest, Extraversion (E) and Openness (O) were studied. It is difficult to conceive that the other three traits might logically be related to the willingness to use expert systems.

Relationships between personality and intelligence have increasingly gained attention from psychologists (Saklofske and Zeidner, 1995; Sternberg and Ruzgis, 1994). For example, McCrae (1987) found that the Openness (O) domain was more related to creativity and divergent thinking than other domains, and Ferguson and Patterson (1998) found that the Openness (O) domain was more strongly correlated with problem solving through challenge (typical intellectual engagement measure) than other domains. Consequently, extension agents' intelligence was taken into account as an external variable in addition to their attitudes towards POSOP' s features, and personality traits.

For the intelligence concept to be included in the model, the Triarchic Theory of Intelligence (Sternberg, 1985, 1988) is preferable as it emphasises information processing of human beings as an important component of intelligence. On the other hand, the TPB emphasises actually making use of the information available. Both processes are indispensable for decision-making before any action is taken. Extension agents categorised with the same personality domain might hold different attitudes towards the use of POSOP due to different intelligence levels, or different information processing ability, and thus use POSOP to different levels.

As mentioned earlier, intelligence comprises analytical, creative, and practical thinking abilities. The theory emphasises the processing of information which can be viewed in terms of three kinds of highly interdependent components: metacomponents, performance, and knowledge-acquisition components.

Suppose an extension agent was asked to solve a farmer's disease problem. He would probably use his analytical thinking ability to identify the causes of the disease, then use metacomponents to plan a solution to the problem, monitor the solutions, and evaluate how well the solutions worked. If it is a familiar disease, he would try to solve it by applying what is known, and thus use performance components for giving advice to a farmer on the course of action to be taken in solving the problem. If it is an unfamiliar disease, or new, he would use knowledge-acquisition components to find out whether the disease has occurred somewhere else and how the treatment problem can be resolved. He would also use analytical thinking to compare the situation with others, and decide whether the solution to other situations might be applicable, before giving guidance to the farmer. If the problem has never occurred before, creative thinking would come into play and research would be needed into the causes of, and solutions to, the problem.

In practice, if he cannot identify the disease, he would collect the diseased plants from the field and take them to a plant pathologist, or a plant pathologist would call to the field to identify the disease. Since plant pathologists are scarce and may not be available when needed, if he is offered POSOP as an alternative support tool to compensate for the scarce plant pathologists, he would use all three components to weigh the advantages and disadvantages of using POSOP.

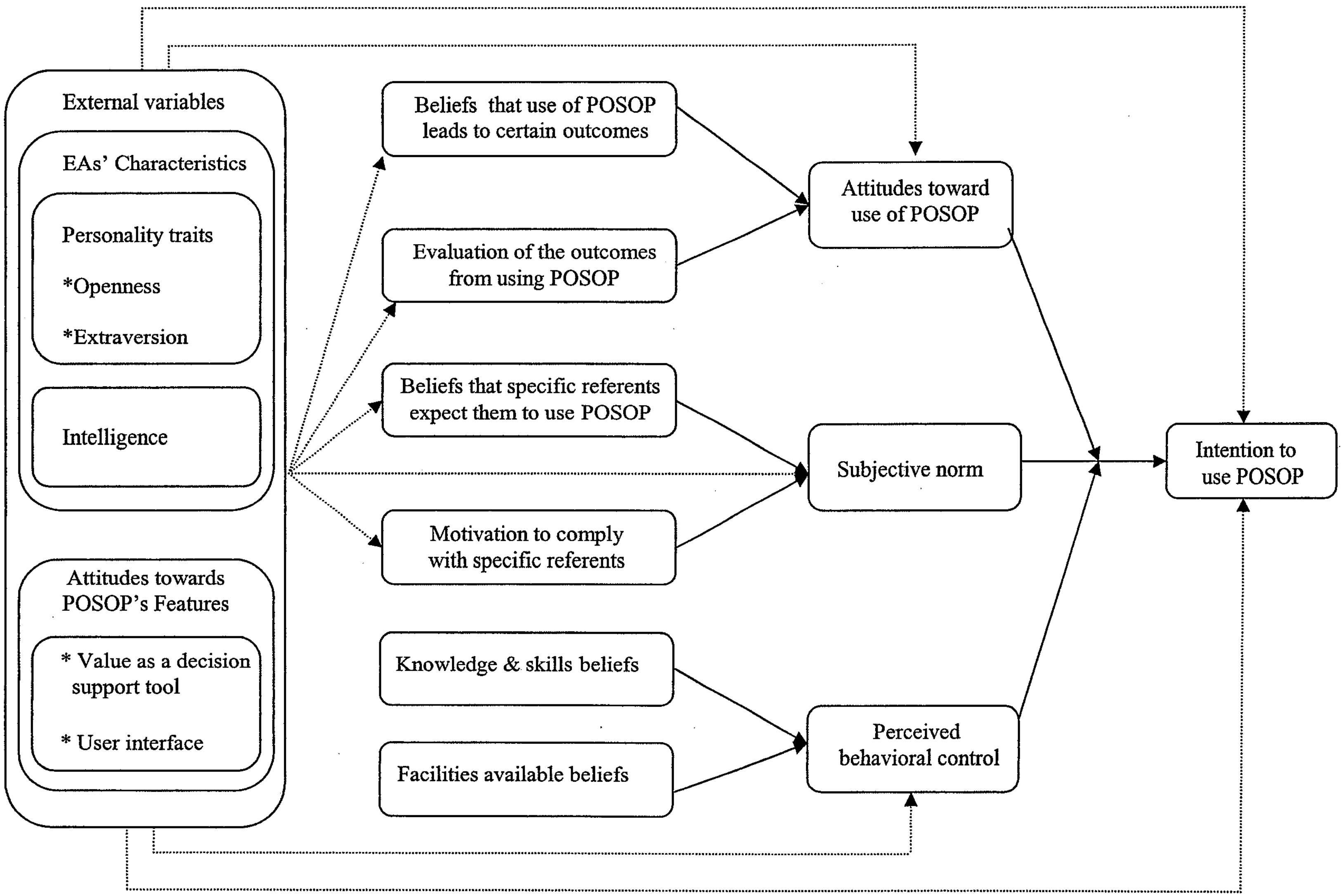
The conceptual model (Figure 4.5) of the factors explaining extension agents' attitudes towards use of expert systems defined earlier, proposes that extension agents' intention to use expert systems (in particular POSOP) is determined by (i) their attitudes towards the use of POSOP, (ii) their subjective norm or perceived social pressure on them to use POSOP, and (iii) their perceived behavioural control over using POSOP, or perceived difficulty of using POSOP.

The beliefs underlying their attitudes towards use of POSOP (their beliefs that the use of POSOP leads to certain outcomes, and the evaluation of the outcomes) directly influence their attitudes. The beliefs underlying their subjective norm (their beliefs with regard to specific referents expecting them to use POSOP and their motivation to comply with specific referents) directly influence their subjective norm. The beliefs underlying their perceived behavioural control over using POSOP (beliefs about their knowledge and skills in, and the facilities available for, using POSOP) directly influence to their perceived behavioural control.

The external variables that are likely to help to explain extension agents' attitudes towards the use of POSOP were POSOP's features (value as a decision support tool and its user interface), personality traits (Extraversion (E) and Openness (O)), and intelligence. They are likely to directly, or indirectly influence their intention to use POSOP via their attitude and subjective norm, or via the beliefs underlying their attitudes and subjective norm.

For POSOP use, extension agents might think, for example, that its use would be a convenient way to obtain information, save time in searching for information, enhance their knowledge and skills, provide confidence in giving advice, and thus generally enhance their extension efficiency. On the other hand, they might think that their own knowledge and experiences, as well as information from other sources, would be more useful. When a POSOP diagnosis conflicts with their own diagnosis, they might conclude that POSOP might not only confuse their understanding but also threaten their job. These were collectively defined as 'behavioural belief.' Generally speaking, extension agents will

**Figure4.5** A conceptual model of attitudes of extension agents (EAs) towards use of an expert system for rice disease diagnosis and management (POSOP).



consider the implications of their use of POSOP before they decide to use it. They will also evaluate possible outcomes from using POSOP. Both their behavioural belief and their evaluation of outcomes from using POSOP directly influence their attitudes towards using it. Clearly, the more positive the beliefs with regard to using POSOP, the more positive the evaluation of outcomes, the stronger the intention to use POSOP.

In regard to the subjective norm, since all extension agents are attached to the Department of Agricultural Extension (DOAE), and they exchange their knowledge and experiences with their peers, as well as give advice to farmers, their organisation, their peer group, and the farmers must all be considered as significant others (or specific referents). They might perceive, for example, that the DOAE would rather they use POSOP as a decision support tool to compensate the scarcity of experts in rice disease. Similarly, they might perceive that their peers would rather they use POSOP if it is considered helpful to support faster and timely decision making and as a double check on their diagnosis. Similarly, they might also perceive that progressive farmers would rather that they use POSOP to help solve their problems in a rapid and more timely manner. On the other hand, traditional farmers might disagree due to a lack of confidence in computer diagnosis and advice. All these factors were defined as their 'normative belief,' which, together with their motivation to comply with significant others, directly influences their subjective norm. Clearly, the stronger 'the significant others' expect them to use POSOP, and the stronger their motivation to comply with the 'significant others,' the stronger the intention to use POSOP.

For perceived behavioural control, the control beliefs depend partly on the agents' perception of their own knowledge and skills in using POSOP (such as computer skills), and partly on the facilities available for using POSOP (such as a computer with POSOP loaded). They might perceive that they have poor computer skills and, thus difficulty in using POSOP, or they might also be concerned about the access to a suitable computer.

In summary, the proposed hypotheses are:

Hypothesis 1: Extension agents' attitudes towards the use of POSOP, together with their subjective norm, and their perceived behavioural control all directly influence their intention to use POSOP.

Hypothesis 2: Extension agents' attitudes towards POSOP's value as a decision support tool together with its user interface directly, or indirectly, influence (i) their attitudes towards the use of POSOP, (ii) their subjective norm, and (iii) their intention to use it.

Hypothesis 3: Extension agents' personality traits (Extraversion (E) and Openness (O)) directly, or indirectly, influence (i) their attitudes towards the use of POSOP, (ii) their subjective norm, and (iii) their intention to use it.

Hypothesis 4: Extension agent's intelligence directly, or indirectly, influences (i) their attitudes towards the use of POSOP, (ii) their subjective norm, and (iii) their intention to use it.

# CHAPTER 5

# Research Design and Methods

## 5.1 Introduction

In Chapter 4, a conceptual model of extension agents' attitudes towards the use of an example expert system (POSOP) was proposed. In this chapter the conceptual model is put into operation. Thus, the research design and methods, as well as data analysis, are presented in this chapter. Finally, a structural equation and measurement model, and its analysis, are discussed.

## 5.2 Research Design

Although the proposed model of expert system acceptance was based on the TPB framework, structural equation modelling (Bollen, 1989) was used instead of the expectancy-value model. Conner and Armitage (1998, p. 1453) suggested that

> "The uses of the TPB are based on the assumption that the TPB describes a causal process. However, to date, relatively few studies have addressed this assumption, most relying on correlational data among self-report measures. Further research demonstrating the causal relationships among the variables in the TPB and any expansions to it is clearly required."

The reasons for using structural equation modelling are that: (1) this study not only attempts to predict, but also to explain extension agents' psychological processes underlying their use of POSOP. The acceptance process unfolds once the agents' beliefs that underlie their attitude to the use of POSOP (AT), their subjective norm (SN), and their perceived behavioural control (PBC) are traced; (2) structural equation model provides the holistic view of a series of simultaneously interdependent relationships; and (3) structural equation modelling has been recently used in TPB analysis (Rhodes, Courneya, and Jones, 2002; Rhodes and Courneya, 2003a; Rhodes and Courneya, 2003b).

## 5.3 Research Methods

### 5.3.1 Subjects

As the research problem concerns extension personnel and extension work in Thailand, the subjects were agricultural extension officers in the Department of Agricultural Extension (DOAE).

### 5.3.2 Sample Size

A size sufficient to produce reliable results was problematic. Clearly, the more subjects the better, though this depends on the accuracy required. Guilford (1954) argued that 200 was a minimum figure, but Kline (1994) argued that this was pessimistic. In data with a clear factor structure, samples of 100 were quite sufficient. The difficulty is that prior knowledge of the data variability is not available so determining an appropriate sample size in a statistical sense is difficult. However, under resource and time constraints, a manageable sample might need to be less than theoretically desirable.

For statistical determination reasons it is essential that there are more subjects than variables, and beyond this minimum there have been various claims concerning the ratio of subjects to variables running from as large as 10:1 as the necessary minimum, down to 2:1 (Kline, 1994). In this case, it is desirable to select variables strategically to cover the personality and ability domains (Boyle, Stankov, and Cattell, 1995). The general rule of thumb is that a minimum 10 subjects per variable is required to obtain factor pattern solutions (Gorsuch, 1983), but this must still depend on the subject variability that exists.

In this study, there were 15 variables in the proposed model:

(1) five independent variables external to the TPB:

- attitude towards POSOP' s value as a decision support tool (VAL),
- attitude towards POSOP' s user interface (UI),
- Extraversion (E),
- Openness (O), and
- Intelligence (GPA);

(2) ten variables based on the TPB:

nine independent variables;

- beliefs that use of POSOP leads to certain outcomes (BB),
- evaluation of the expected outcomes (EO),
- beliefs that specific significant others expect them to use POSOP (SO),
- motivation to comply with their specific significant others (MS),
- beliefs about their own knowledge and skills in using POSOP (KSK),
- beliefs about the facilities available for using POSOP (FAV),
- attitudes towards use of POSOP (AT),
- subjective norm (SN),
- perceived behavioural control (PBC), and

one dependent variable;

- intention to use POSOP (I).

### 5.3.3 Sampling Subjects

One extension officer was randomly selected from each District Agricultural Office in the Central plain and Western Thailand as both regions are rice production areas. The Central plain region is an intensive rice production area (2 crops/year) while the Western region is extensive (1 crop/year). Lists of extension officers in the Central plain and Western regions were supplied by the Department of Agricultural Extension. One hundred and thirty-five extension officers were randomly selected, 74 from the Central plain, and 61 from the Western regions. Thus the subject to variable ratio was 9:1.

## 5.4 Measures

### 5.4.1 Personality Traits

The FFM is normally either measured by the NEO PI-R (240-item version, – 48 for each of the five domains, each domain consists of six facets – lower-level traits – each of which are assessed by 8 items), or the NEO-FFI (60-item version of Form S of the NEO PI-R; each domain consists of five 12-item scales that measure each domain). The NEO-FFI provides a brief but comprehensive measure of the five domains of personality. Information on specific facets within each domain is not provided, and the shortened scales are somewhat less reliable than the full NEO PI-R (Costa and McCrae, 1992b). The NEO PI-R is usually completed within 45 minutes while the NEO-FFI requires 10-15 minutes to complete. Due to time constraints, and the lack of a need to consider the facets, the NEO-FFI was used to measure the personality of the agricultural extension officers.

### 5.4.2 Intelligence

It would be desirable to measure intelligence using Sternberg's Triarchic Abilities Test (STAT), which yields a total score and separate scores for each ability that corresponds to each aspect of intelligence proposed by his Triarchic Theory of Intelligence. However, Sternberg states that "STAT is neither immune to effects of prior learning nor is it free of cultural impacts, as intelligence cannot be tested outside the boundaries of a culture" (http://www.newhorizons.org/future/ Creating_the_Future/crfut_sternberg.html, 2003).

Sternberg et al. (2000) claim that the STAT is not related to, nor a measure of, general intelligence. However, in a recent study, Koke and Vernon (2003) used introductory psychology midterm examination grades, STAT scores, and Wonderlic Personnel Test scores (as a measure of general intelligence). They found that total STAT scores and each of the STAT subsection scores were significantly related to Wonderlic test scores. The total STAT and practical subsection scores significantly predict academic achievement (midterm grades), independent of general intelligence; however, the analytical and creative subsection scores do not. As a Thai version of STAT was not available, the agent's Grade Point Average (GPA) was used as a proxy for their intelligence. Thus, it was assumed the officers' intelligence was correlated with their formal GPA, which can be thought of as the results from their information processing in formal education.

### 5.4.3 Extension Agents' Attitudes towards POSOP' s Features and the TPB Variables

A questionnaire (see Appendix E) was developed to measure the extension officers' attitudes towards POSOP' s features – its value as a decision support tool (VAL) and its user interface (UI). Their intention to use POSOP (I), and the values of the determinants of intention; their attitude towards the use of POSOP (AT), subjective norm (SN), or perception of generalized significant others' pressures on them to use POSOP, and perceived behavioural control over using POSOP (PBC) were also measured. Also measured by the questionnaire were the determinants of these factors (their beliefs with regard to using POSOP (BB), and view on expected outcomes from using POSOP (EO), their beliefs with regard to specific significant others expecting them to use POSOP (SO), and their motivation to comply with significant others (MS), knowledge and skill in using POSOP (KSK), and the facilities available for using POSOP (FAV).

## 5.5 Data collection

Data collection was carried out between November, 2001 and April, 2002 by means of a mail survey and a workshop. The questionnaire, NEO-FFI, and POSOP CDs with installation sheets were sent to 135 agricultural extension officers in the Central plain and Western Thailand in February, 2002. The officers were asked to try using POSOP, and then answer the questionnaire and NEO-FFI. The workshop was run on March 16, 2002 for an additional 107 agricultural extension officers involved in a pilot project of the Ministry of Agriculture and Cooperatives at the National Agricultural Extension and Training Centre and the Faculty of Agriculture computer laboratory, Kasetsart University, Kamphaengsaen campus, Nakhon Pathom province. The participants were attending a one-hour session of "Information Technology: An Expert System (POSOP) as a Decision Support Tool" and consecutively participating in a two-hour workshop on "How to Use POSOP." Then, they were asked to complete the same questionnaire and NEO-FFI used in the mail survey after the workshop.

Note that the workshop was not an originally planned data collection method. Due to unforeseen circumstances, by the time data were being collected the extension officers met in response to an urgent need to register farmers in their areas of responsibility (required by the Ministry of Agriculture and Cooperatives). The extension officers participating in the workshop came from District Agricultural Offices throughout Thailand, and were not randomly selected. However, the gathering was an ideal opportunity to collect additional data. Thus the data obtained were mixed between the random mail survey and the workshop. While this may have affected the distribution of data and the inference made about the population as a whole, the additional data will have improved the statistical reliability of the conclusions. The full list of data collected and variables studied, and their details, are given in Tables 5.1 - 5.5.

**Table 5.1** Extension agents' background relevant to the explanation of their attitudes towards the use of POSOP.

| Variable | Definition | Unit | Type | Comments |
|---|---|---|---|---|
| Gender | Gender of extension agents | 1 – 2 score | Binary | Item no. E1, 1 = male, 2 = female |
| Age | Age of extension agents | Years | Numeric | Item no. E2 |
| Experience | Years of experience as an extension agent | Years | Numeric | Item no. E3 |
| Certificate Major | Major of a certificate under bachelor degree | | String | Item no. E42 |
| Bachelor Major | Major of a bachelor degree | | String | Item no. E52 |
| Master Major | Major of a master degree | | String | Item no. E62 |

**Table 5.2** Extension agents' personality traits.

| Variable | Definition | Unit | Type | Comments |
|---|---|---|---|---|
| **N** | Neuroticism | 0 – 4 score | Numeric | Sum of item no.* 1, 6, 11, 16, 21, 26, 31, 36, 41, 46, 51 & 56. |
| **E** | Extraversion | 0 – 4 score | Numeric | Sum of item no.* 2, 7, 12, 17, 22, 27, 32, 37, 42, 47, 52 & 57. |
| **O** | Openness | 0 – 4 score | Numeric | Sum of item no.* 3, 8, 13, 18, 23, 28, 33, 38, 43, 48, 53 & 58. |
| **A** | Agreeableness | 0 – 4 score | Numeric | Sum of item no.* 4, 9, 14, 19, 24, 29, 34, 39, 44, 49, 54 & 59. |
| **C** | Conscientiousness | 0 – 4 score | Numeric | Sum of item no.* 5,10,15, 20, 25, 30, 35, 40, 45, 50, 55 & 60. |

* Item numbers are from the NEO-FFI. This is not included in the report due to the copyright protection.

**Table 5.3** Extension agents' intelligence.

| Variable | Definition | Unit | Type | Comments |
|---|---|---|---|---|
| Certificate GPA **(CGPA)** | Grade Point Average of a certificate under bachelor degree | 0 – 4 scale | Numeric | Item no. E4.1 |
| Bachelor GPA **(BGPA)** | Grade Point Average of a bachelor degree | 0 – 4 scale | Numeric | Item no. E5.1 |
| Master GPA **(MGPA)** | Grade Point Average of a master degree | 0 – 4 scale | Numeric | Item no. E6.1 |

**Table 5.4** Extension agents' intention, attitudes, subjective norm, and perceived behavioural control with regard to the use of POSOP.

| Variable | Definition | Unit | Type | Comments |
|---|---|---|---|---|
| **I** | Intention to use POSOP | 0 – 4 score | Numeric | Item no. I |
| **AT** | Attitudes towards the use of POSOP | 0 – 4 score | Numeric | Average of item no. A12 & A23 |
| **SN** | Perception of generalised significant others' pressures on them to use POSOP | 0 – 4 score | Numeric | Item no. A16 |
| **PBC** | Perception of generalised difficulty in using POSOP | 0 – 4 score | Numeric | Item no. B4 |
| **BB** | Beliefs that use of POSOP leads to certain outcomes | 0 – 4 score | Numeric | Average of item no. A2, A3, A4, A7, A11, A13, & A14 |
| **EO** | Views on expected outcomes from using POSOP | 0 – 4 score | Numeric | Average of item no. A1, A5, A6, A8, A9, A10, & A22 |

**Table 5.4** Extension agents' intention, attitudes, subjective norm, and perceived behavioural control with regard to the use of POSOP (cont.).

| Variable | Definition | Unit | Type | Comments |
|---|---|---|---|---|
| **SO** | Beliefs with regard to specific significant others expecting them to use POSOP | 0 – 4 score | Numeric | Average of item no. A19, A20, & A21 |
| **MS** | Motivation to comply with their specific significant others | 0 – 4 score | Numeric | Average of item no. A15, A17, & A18 |
| **KSK** | Beliefs with regard to their own knowledge and skills in using POSOP | 0 – 4 score | Numeric | Average of item no. B6 & B14 |
| **FAV** | Beliefs with regard to the facilities available for using POSOP | 0 – 4 score | Numeric | Average of item no. B7 & B13 |

**Table 5.5** Extension agents' attitudes towards POSOP's value and its user interface.

| Variable | Definition | Unit | Type | Comments |
|---|---|---|---|---|
| VAL | Attitudes towards POSOP's value as a decision support tool | 0-1 | Numeric | Average of item no. C1, C2, C3, & C6 |
| UI | Attitudes towards POSOP's user interface | 0-1 | Numeric | Average of item no. C4, C5, C7, C8, C9, C10, C11, C12, & C13 |

## 5.6 Data Analysis

The responses from the mail survey and the workshop are summarised in Table 5.6. The response rates were 36% (49 from the mail survey) and 88% (94 from the workshop). Of those responses, there was a total of 130 valid responses (answering both the NEO-FFI and the questionnaire), 39 and 91 from the survey and the workshop, respectively. The invalid responses (answering either the NEO-FFI or the questionnaire, insincere answering and making wrong choices in the NEO-FFI, and not having tried using POSOP) of 13 subjects were excluded from the analysis.

**Table 5.6** Responses from the mail survey and the workshop.

| | **Mail survey** | **Workshop** | **Total** |
|---|---|---|---|
| Total mail sent/total participants | 135 | 107 | 242 |
| Response | 49 | 94 | 143 |
| Response rate (%) | 36 | 88 | - |
| Answering the NEO-FFI only | 2 | 1 | 3 |
| Answering the questionnaire only | 4 | 1 | 5 |
| Making wrong choice in the NEO-FFI | - | 1 | 1 |
| Insincere answering the NEO-FFI | 2 | - | 2 |
| Not having tried using POSOP | 2 | - | 2 |
| Valid response | 39 | 91 | 130 |

Firstly, the data were analysed to detect data entry errors and outliers. Secondly, the scores for each variable were summated, and the summated scale scores were analysed to ensure the adequacy of their reliability before fitting into the structural equation model. Finally, the proposed model was analysed.

### 5.6.1 Preliminary Data Analysis.

Descriptive statistics calculated by SPSS (SPSS, 1999) were used as a preliminary description of the extension agents' background and opinions about POSOP and expert systems in general, and the variables studied.

### 5.6.1.1 Extension Agents' Background and Opinions about POSOP Use and Expert Systems in General

Of the extension agents, twenty- three percent (30) were female and, thus, seventy-seven were male. Their average age was 44 ($\pm$ 4.27 SD) years with an average of 20 ($\pm$ 4.64 SD) years experience as an extension officer (Table 5.7). On average they were middle-aged and experienced. Although the male to female ratio of the survey and the workshop were somewhat different, their ages were quite similar (46 $\pm$ 5.78 SD and 43 $\pm$ 2.88 SD), as with their years of experience (22 $\pm$ 6.04 SD and 19 $\pm$ 3.51 SD).

**Table 5.7** Extension agents' gender, age, and experience.

| **Gender** | **Number** | | | **Percent** | | |
|---|---|---|---|---|---|---|
| | **Survey** | **Workshop** | **Total** | **Survey** | **Workshop** | **Total** |
| Male | 34 | 66 | 100 | 87.2 | 72.5 | 76.9 |
| Female | 5 | 25 | 30 | 12.8 | 27.5 | 23.1 |
| **Total** | 39 | 91 | 130 | 100 | 100 | 100 |
| **Age and Experience (years)** | **Average** | | | **SD** | | |
| | **Survey** | **Workshop** | **Both** | **Survey** | **Workshop** | **Both** |
| Age (N = 129) | 46.47 | 42.77 | 43.87 | 5.78 | 2.88 | 4.27 |
| Years of experience (N = 127) | 22.26 | 19.06 | 20.02 | 6.04 | 3.51 | 4.64 |

Table 5.8 gives the areas in which the extension agents trained. At certificate level, most studied plant science and technology, with only a few studying economics and extension. In contrast, at bachelor degree level, 66.7% majored in agricultural extension.

At the masters degree level, however, the areas were more mixed with 33.3% having majored in plant or crop science, 33.3% in political science, 16.7% in agricultural development, and 16.7% in social policy and planning. While it is noted that plant pathology was not their major it could have been a component of their plant and crop science degrees.

**Table 5.8** Extension agents' major at certificate, bachelor, and masters level.

| Major | Certificate Percent (N=104) | Bachelor Percent (N=94) | Masters Percent (N= 6) |
|---|---|---|---|
| 1. Plant/Crop Science | 43.3 | 6.7 | 33.3 |
| 2. Agriculture/Agricultural Technology | 26.0 | 11.1 | |
| 3. Animal Science | 10.6 | | |
| 4. Agribusiness | 5.8 | | |
| 5. Agricultural Economics | 5.8 | | |
| 6. Agricultural extension | 3.8 | 66.7 | |
| 7. Agriculture and cooperatives | | 6.67 | |
| 8. Home economics/community nutrition | 2.0 | 3.3 | |
| 9. Fishery | 1.0 | | |
| 10. Rice | 1.0 | | |
| 11. Agricultural mechanics | 1.0 | | |
| 12. Education | | 1.1 | |
| 13. Law | | 1.1 | |
| 14. Arts | | 1.1 | |
| 15. Sciences | | 1.1 | |
| 16. Administration and Management | | 1.1 | |
| 17. Political Science | | | 33.3 |
| 18. Agricultural Development | | | 16.7 |
| 19. Social Policy and Planning | | | 16.7 |

The agents' opinions about POSOP' s general features (see Appendix F), both good and bad, are likely to be related to their intention to use it. Obviously, its good features (Table F1) include (1) ease and convenience of use, (2) provision of quick diagnosis and timely decision support, (3) ease of understanding, and (4) clarity of pictures and text. There were a small number of bad features (Table F2), some of which can be easily fixed (such as an increase in the size of pictures displayed), whereas others require greater time and effort to fix (such as expanding the knowledge base to cover more diseases and providing further explanations).

Their opinions about POSOP use and expert systems in general are summarised in Table 5.9. The respondents were, in general, in favour of using POSOP (89.7%) (see Table F3 for the reasons). The reasons for not using it were lack of (i) available computer facilities, (ii) basic computer skills, and (iii) a supporting budget (see Table F4).

Surprisingly, ninety-eight percent would use POSOP to train themselves in rice disease diagnostic skills (see Table F5 for the reasons). This revealed the important role of expert systems as a training tool in addition to their direct decision support role. Another one percent would not use POSOP as their area of responsibility was not in rice production. The other one percent would not use POSOP at all, or use only if their knowledge proved inadequate. A comment was made that if POSOP was used in the first instance, sooner or later their own skills would be lost.

**Table 5.9** Extension agents' opinions about POSOP use and expert systems in general.

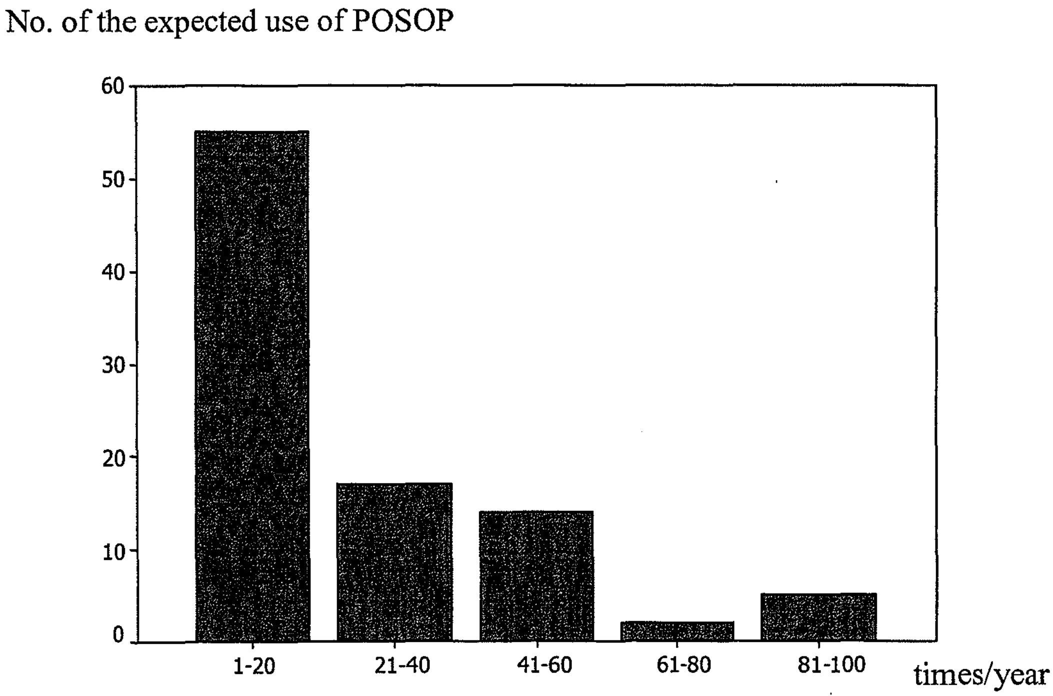
| Statement | Percent indicating: | | |
|---|---|---|---|
| | Y | N | Y&N |
| Would you use POSOP? (N = 126) | 89.7 | 10.3 | - |
| Would you use POSOP to train yourself in rice disease diagnostic skills? (N = 120) | 98.3 | 0.8 | 0.8 |
| Would you use POSOP with a farmer beside you? (N = 121) | 78.5 | 0.8 | 20.7 |
| Do you a think a wide range of well-prepared expert systems have a potential for helping extension officers? (N = 122) | 98.4 | 1.6 | - |
| Should your office support the development of many more expert systems? (N = 123) | 96.7 | 2.4 | 0.8 |

In assessing the impact of a 'significant other', the question "Would you use POSOP with a farmer beside you?" was asked. The agents' response to this question was qualified. Seventy-nine percent would use POSOP if the farmers came to their offices, whereas twenty-one percent noted they would not use POSOP if they visited the farmers as they did not have a portable computer (see Table F6 for the reasons). Only one percent would not use POSOP due to a fear of losing credibility.

For expert systems, 98.4% believed a wide range of well-prepared expert systems had the potential to help (see Table F7 for the reasons). The remainder commented that extension agents would have no idea about the potential of expert systems without extensive experience using POSOP. Furthermore, if there was no budget to support POSOP use, there was no benefit in promoting their use. Whether their offices would in fact support the development of more expert systems, 96.7% agreed that support should be provided (see Table F8 for the reasons).

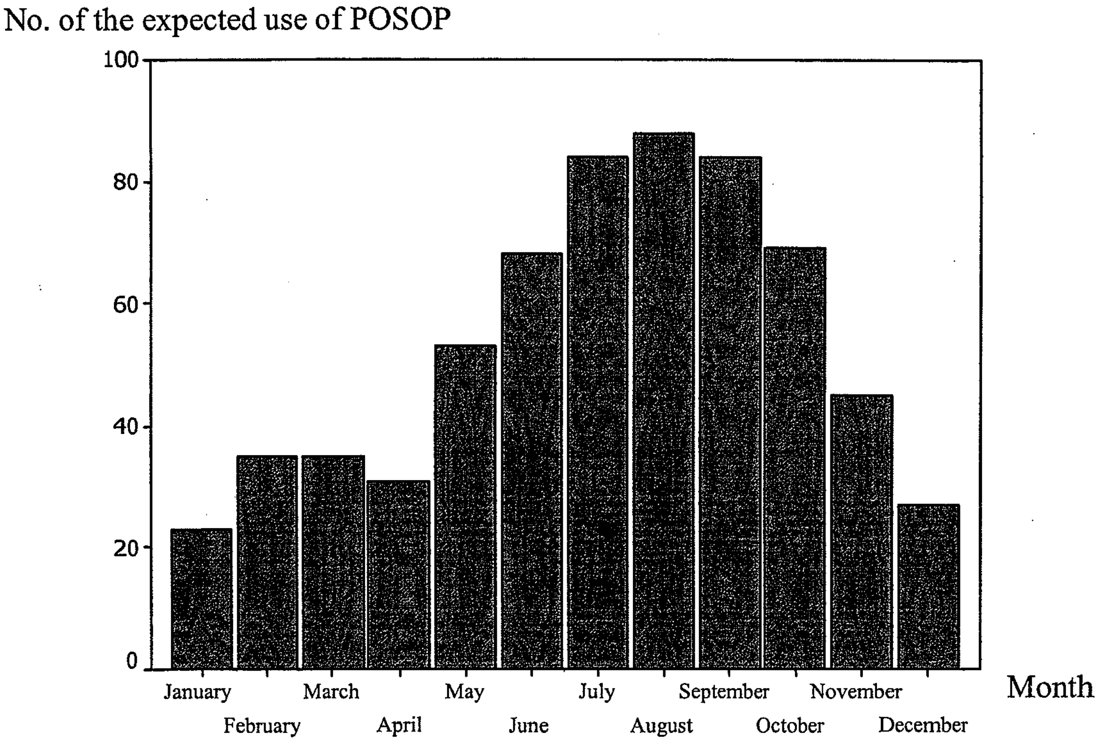
However, support of POSOP or any other expert system development must be justified. Number and pattern of the expected use of POSOP in a year can be used as criteria for justifying support of further development and use of POSOP. When asked how often they would use POSOP in a year, ninety-three extension agents answered. Of those, more than half (55 or about 60%) of the agents would use POSOP 1-20 times a year. The rest, 17, 14, 2, and 5 agents, would use POSOP 21-40, 41-60, 61-80, and 81-100 times/year, respectively (Figure 5.1).

**Figure 5.1** Number of the expected use of POSOP in a year.



When asked which months they would use POSOP in a year, as might be expected, POSOP would be frequently used between May and October as this time of the year is in-season rice production. The most frequent use of POSOP fell in mid rainy season or August. Outbreaks of many rice diseases can be expected in the rainy season as the hot and humid conditions are suitable for many pathogen and vector growths. In contrast, POSOP would be less frequently used between December and April as this time of the year is off-season rice production and the weather conditions are cold and dry in December and hot and dry in April. The most frequent use of POSOP in off-season rice production fell in February and March where the first rain comes (Figure 5.2).

**Figure 5.2** Pattern of the expected use of POSOP in a year.




The respondent who did not support further development commented that he did not see the importance or necessity of the systems, believing his own competence was adequate. Furthermore, being in a small office with a limited budget and personnel it was believed money should not be diverted. This suggested, assuming positive benefits, systems development should be supported by a higher level office (perhaps, the Provincial Office, the Regional Office, or the Department of Agricultural Extension). The one respondent who was undecided said the development of expert systems should be supported only if the systems were considered very useful.

#### 5.6.1.2 Extension Agents' Attitudes towards POSOP' s Value (VAL) and Its User Interface (UI)

As none of the agents were plant pathologists, as might be expected, extension agents' attitudes towards POSOP' s value as a decision support tool (VAL) and its user interface (UI), were positive or favourable (Table 5.10).

**Table 5.10** Extension agents' attitudes towards POSOP' value and its user interface.

| Variable | Average[a] score | SD |
|---|---|---|
| Attitude towards POSOP's value (VAL) | 3.40 | 0.39 |
| Attitude towards POSOP's user interface (UI) | 3.16 | 0.46 |

[a] Scores range from 0 to 4, where 0 = strongly disagree, 1 = disagree, 2 = neutral, 3 = agree, and 4 = strongly agree.

#### 5.6.1.3 Extension Agents' Personality Traits

The summated scale scores for each of the five domains, Neuroticism (N), Extraversion (E), Openness (O), Agreeableness (A), and Conscientiousness (C) were obtained by summing the values of the responses to the items in the NEO FFI (see Table 5.2). The scores of each item range from 0 to 4 and there are 12 items in each domain, thus the total scores of each domain range from 0 to 48.

To characterise the agents' personality traits, *T* scores (a type of score based on the transformation of normalised standard scores to a scale based on a mean of 50 and a standard deviation of 10; Costa and McCrae, 1992b) of each domain were calculated. Figure 5.3 displays distributions of *T* scores for the five domains. All scales were tested for normality using the Kolmogorov-Smirnof statistic with Lilliefors Significance correction (Table 5.11). If the significance level is greater than 0.05, then normality can be assumed. In this sample, three out of five domains, Neuroticism (N), Extraversion (E), and Agreeableness (A), were assumed to have a normal distribution.

**Figure 5.3** Distributions of $T$ scores for the five domains.

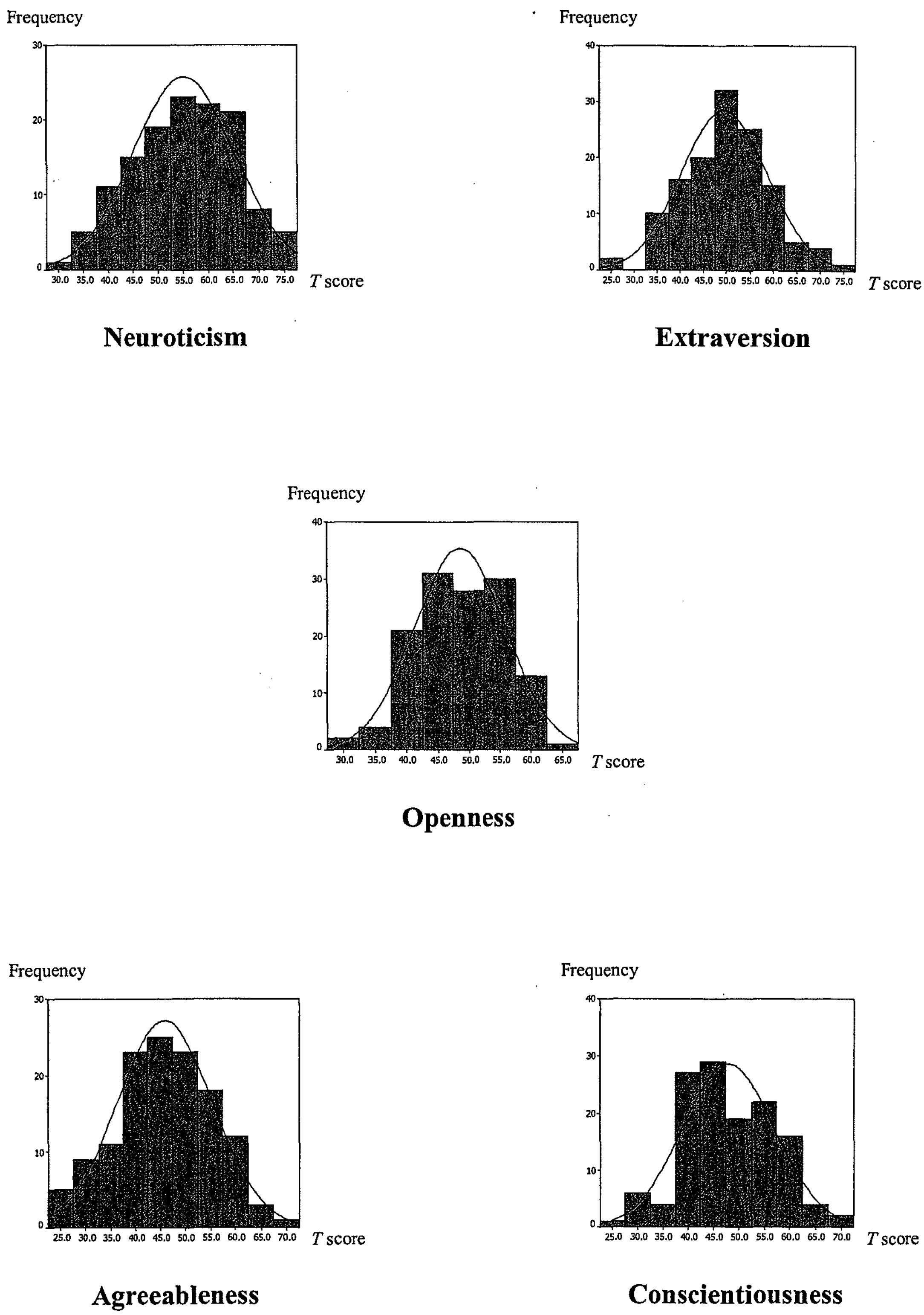


**Table 5.11** Tests of normality of *T* scores for the five domains.

| Domain | Kolmogorov-Smirnov[a] | | |
|---|---|---|---|
| | **Statistic** | **Df** | **Sig.** |
| Neuroticism (N) | .074 | 130 | .075* |
| Extraversion (E) | .068 | 130 | .200* |
| Openness (O) | .090 | 130 | .012 |
| Agreeableness (A) | .057 | 130 | .200* |
| Conscientiousness (C) | .101 | 130 | .002 |

* This is a lower bound of the true significance.

[a] Lilliefors Significance correction.

As the research interest focused on the Extraversion (E) and Openness (O) domains, only those two domains were used in the structural equation model.

#### 5.6.1.4 Extension Agents' Intelligence

Average GPAs obtained from certificate, bachelor, and masters degrees were 2.83, 2.58, 3.26 respectively (Table5.12). The GPA obtained from the certificate level was significantly, but moderately, correlated with those obtained from bachelor degrees ($r = 0.25$). As most extension agents provided their GPAs from the certificate level, these GPAs were used in the structural equation modelling.

**Table 5.12** Extension agents' grade point average (GPA) at certificate, bachelors, and masters degrees.

| Grade Point Average (GPA) | Average | SD |
|---|---|---|
| Certificate (N = 106) | 2.83 | 0.45 |
| Bachelors degrees (N = 86) | 2.58 | 0.33 |
| Masters degrees (N= 5) | 3.26 | 0.42 |

### 5.6.1.5 Extension Agents' Intention, Attitudes, Subjective Norm, and Perceived Behavioural Control and Their Determinants

Generally speaking, extension agents' intentions to use POSOP (I) as a decision support tool were strong (see Table 5.13). Their attitude towards the use of POSOP (AT) and its determinants, their belief with regard to using POSOP (BB), and their evaluation of expected outcomes from using POSOP (EO), were all positive or favourable, with means of 3.63, 3.40, and 3.65 respectively.

Although their belief with regard to specific significant others expecting them to use POSOP (SO), and their motivation to comply with their significant others (MS), were reasonably strong, with means of 3.15 and 2.98, their perception of generalised significant others' pressures on them to use POSOP (SN) was weaker at 2.60 (all out of 4).

Their perception of generalized control over using POSOP (PBC), and beliefs in their own knowledge and skills (KSK) in using POSOP, were high, with means of 1.43 and 1.29 out of 4 (reverse-scored), while their perception of the facilities available for using POSOP was neutral (2.00). In other words, they perceived that they would not have difficulty in using POSOP and believed that using or operating a computer, or using POSOP, would not be difficult, though they believed that they had poor computer skills (2.99, not shown in the table). However, they were not sure about the facilities available for using POSOP.

### 5.6.2 Reliability Analysis

Some concepts or constructs are not perfectly measured by a single item. Thus summated scale scores were created from the items in the questionnaire. Reliability analysis was conducted to ensure that the summated scale scores created were adequate or reliable. A commonly used measure of reliability is internal consistency. The rationale for using internal consistency is that the individual items on the scale should all be measuring the same construct or concept and thus be highly inter-correlated (Hair et al., 1998).
There are several measures relating to each separate item, including the item-to-total correlation (the correlation of an item to the summated scale score) or the inter-item correlation (the correlation among items). "Rules of thumb" suggest that the item-to-total correlation should exceed 0.5 and that the inter-item correlation should exceed 0.3 (Hair et

**Table 5.13** Extension agents' intention, attitudes, subjective norm, and perceived behavioural control and their determinants.

| Variable | Average[a] score | SD |
|---|---|---|
| Intention to use POSOP (**I**) | 3.72 | 0.49 |
| Attitudes towards the use of POSOP (**AT**) | 3.63 | 0.47 |
| Beliefs with regard to using POSOP (**BB**) | 3.40 | 0.42 |
| Evaluation of expected outcomes from using POSOP (**EO**) | 3.65 | 0.32 |
| Perception of generalized significant others' pressures on them to use POSOP (**SN**) | 2.60 | 1.22 |
| Beliefs with regard to specific significant others expecting them to use POSOP (**SO**) | 3.15 | 0.64 |
| Motivation to comply with their specific significant others (**MS**) | 2.98 | 0.59 |
| Perception of generalised control over using POSOP (**PBC**) | 1.43 | 0.96 |
| Beliefs in their own knowledge and skills in using POSOP (**KSK**) | 1.29 | 0.67 |
| Perception of the facilities available for using POSOP (**FAV**) | 2.00 | 1.03 |

[a] Scores range from 0 to 4, where 0 = strongly disagree, 1 = disagree, 2 = neutral, 3 = agree, and 4 = strongly agree.

al., 1998). Another measure, the most widely used one, is Cronbach's alpha. The generally agreed lower limit for Cronbach's alpha is 0.7, although it may decrease to 0.6 in exploratory research (Hair et al., 1998). As exploratory research, the Cronbach's alpha with the 0.6 lower limit was used as a criterion in this analysis.

The summated scale scores examined were the extension agents' attitude towards the use of POSOP (AT), POSOP' s value as a decision support tool (VAL), and its user interface score (UI); beliefs with regard to using POSOP (BB), evaluation of expected outcomes from using POSOP (EO), beliefs with regard to specific significant others expecting them to use POSOP (SO), motivation to comply with their significant others (MS), beliefs in their own knowledge and skills in using POSOP (KSK), and the perception of the facilities available for using POSOP (FAV). The extension agent's intention to use POSOP (I), perception of generalised significant others' pressures on them to use POSOP or subjective norm (SN), and perception of generalised control over using POSOP (PBC) were not examined as they are single scale scores. The Cronbach's alphas of the summated scale scores calculated by reliability analysis in SPSS are given in Table 5.14.

The Cronbach's alpha of the summated scale scores ranged from 0.86 (very reliable) to 0.46 (unreliable). The alpha of the extension agents' attitude towards the use of POSOP (AT) and its determinants, beliefs with regard to using POSOP (BB) and evaluation of expected outcomes from using POSOP (EO) were 0.52, 0.69, and 0.69 respectively. Though the alphas of belief with regard to using POSOP (BB), and the evaluation of outcomes from using POSOP (EO), were deemed acceptable, the alpha of the attitude towards the use of POSOP (AT) was beyond the lower limit of acceptability.

**Table 5.14** Cronbach' s alphas of the summated scale scores

| Summated scale scores | Cronbach's alpha |
|---|---|
| Attitude towards the use of POSOP (**AT**) | .52 |
| Beliefs with regard to using POSOP (**BB**) | .69 |
| Evaluation of expected outcomes from using POSOP (**EO**) | .69 |
| Belief with regard to specific significant others expecting them to use POSOP (**SO**) | .80 |
| Motivation to comply with specific significant others (**MS**) | .63 |
| POSOP's value as a decision support tool (**VAL**) | .65 |
| POSOP's user interface (**UI**) | .86 |
| Belief in their own knowledge and skills in using POSOP (**KSK**) | .46 |
| Perception of the facilities available for using POSOP (**FAV**) | .66 |

Thought was given as to how the alpha scores might be improved, or whether other alternatives might be more appropriate. The attitude summated scale score is composed of a 2-item scale: A12 stating, 'My use of POSOP as a decision support tool for rice disease diagnosis and management will be useful.'; and A23 stating, 'I am in favour of using POSOP as a decision support tool for rice disease diagnosis and management.' Although both items were significantly correlated with each other, the magnitude of the correlation was not high ($r = 0.31$) indicating a weak relationship between both items. While item A12 evaluated the extension agents' perceived usefulness of POSOP, item A23 evaluated the agents' attitude towards the use of POSOP. The internal consistency was moderate ($\alpha$ = 0.52). The attitude summated scale score was therefore deemed inappropriate. Using either item as a single scale score may be a more appropriate alternative.

The alphas of the extension agents' belief with regard to specific significant others expecting them to use POSOP (SO), and the motivation to comply with significant others (MS), both fell within the acceptable range with alphas of 0.80 and 0.63.

Similarly, the alphas of the extension agents' attitude toward POSOP's value as a decision support tool (VAL), and user interface (UI) were both within the acceptable range with alphas of 0.65 and 0.86.

Conceptually, control beliefs were related to the difficulty, or ease of, using POSOP. Both the internal, and external controls might play an equally important role in their beliefs. The internal control was a belief in their own knowledge and skills in using POSOP (KSK), whilst the external control was the perception of the facilities available for using POSOP (FAV). Though both concepts are valid, the Cronbach's alpha of their beliefs in their own knowledge and skills (KSK) (0.46) was beyond the lower limit (0.6), while the alpha of their perception of the facilities available (FAV) fell within the acceptable range at 0.66.

Extension agents' belief in their own knowledge and skills in using POSOP (KSK) was significantly correlated with their perception of generalised control over using POSOP (PBC) (r = 0.43); however, there was no correlation between their perception of generalised control over using POSOP (PBC) and their perception of the facilities available for using POSOP (FAV) (r = -0.05). Since the sample size was rather small and the agents' perception of the facilities available was unlikely to be influenced by the external variables (POSOP's value, and user interface, their personality traits, and intelligence), both control beliefs were dropped from the model. This was to avoid fitting too many variables in the model and to ensure the model was parsimonious.

As it appears that results of the personality test (FFM) have not been reported for the Thai culture, it is useful to investigate the results in this sample. The Cronbach alphas of the five domains of the extension agents' personality are given in Table 5.15. In this sample, the Neuroticism (N), Extraversion (E), and Conscientiousness (C) domains seemed to be acceptable, with Cronbach's alphas of 0.75, 0.60, and 0.66, despite the small sample size of 130. However, the Agreeableness (A) and Openness (O) domains were far beyond the acceptable range. Chittcharat (N. Chittcharat, personal communiction, January 2002) also found all domains, except Openness (O), in her Thai university student sample, had acceptable Cronbach scores.

**Table 5.15** Cronbach' s alphas for the five domains of personality.

| Domain | Cronbach' s alpha |
|---|---|
| Neuroticism (N) | .75 |
| Extraversion (E) | .60 |
| Openness (O) | .17 |
| Agreeableness (A) | .41 |
| Conscientiousness (C) | .66 |

Paunonen and Ashton (1998) gave a variety of reasons for not finding a personality scale across cultures. These reasons have to do with the properties of the measure itself, with the nature of the culture being assessed, and with the interaction between the personality measure and the culture. Other reasons include poor test translation, lack of item relevance, trait-level differences, trait-structure differences, differential causal links, response-style involvement, test-format problems, different analytical methods, irrelevant criteria – the criteria used for test validation are not relevant to that culture (for example, an introversion-extraversion measure might be expected, based on theoretical considerations, to predict sensation seeking behaviour).

As this study focused on the Openness (O) domain, the items measuring the Openness (O) domain were investigated. The items were analysed to find out the factor underlying the Openness (O) domain. Using principle component analysis with varimax rotation, five factors were initially extracted, and accounted for 57.7% of the total variance explained (Table 5.16).

---

* Irrelevance refers to the construct not being a concept with in Thai culture.

Component 1, the highest loading factor, accounting for 16.0% of the variance explained, was considered a representative of the Openness (O) domain. Not all of the items loading on component 1 were used in creating the summated scale score. To select among the items, both practical and statistical senses must be taken into account.

As “a rule of thumb,” factor loadings greater than $\pm$ 0.30 are considered to meet the minimal level; loadings of $\pm$ 0.40 are considered more important; and if the loadings are $\pm$ 0.50 or greater, they are considered practically significant. These guidelines are applicable when the sample size is 100 or larger. Statistically, a sample size of 120 with a loading of 0.50, and a sample size of 150 with a loading of 0.45, were considered significant (at a .05 significant level, a power level of 80%, standard errors are assumed to be twice those of conventional coefficients) (Hair et al., 1998). As the sample size of this study was 130, the items with loadings of greater than 0.45 (Table 5.17) were selected as indicators to create the summated scale score for the Openness (O) domain (Table 5.18). However, its internal consistency must also be examined. These items were further analysed using reliability analysis. The Cronbach alphas for the three items was 0.49 compared with 0.17 when using 12 items. Table 5.19 shows Cronbach alphas if an item is deleted. The alphas suggested that dropping any item from the scale would not improve the internal consistency. Thus, the summated scale score created from the three items were used as the Openness (O) variable in the model analysis.

**Table 5.16** Total variance explained – Results from a factor analysis of the personality data.

| Component | Initial Eigenvalues | | | Extraction Sums of Squared Loadings | | | Rotation Sums of Squared Loadings | | |
|---|---|---|---|---|---|---|---|---|---|
| | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % |
| 1 | 1.917 | 16.0 | 16.0 | 1.917 | 16.0 | 16.0 | 1.625 | 13.5 | 13.5 |
| 2 | 1.366 | 11.4 | 27.4 | 1.366 | 11.4 | 27.4 | 1.414 | 11.8 | 25.3 |
| 3 | 1.269 | 10.6 | 37.9 | 1.269 | 10.6 | 37.9 | 1.347 | 11.2 | 36.6 |
| 4 | 1.218 | 10.2 | 48.1 | 1.218 | 10.2 | 48.1 | 1.278 | 10.7 | 47.2 |
| 5 | 1.156 | 9.6 | 57.7 | 1.156 | 9.6 | 57.7 | 1.262 | 10.5 | 57.7 |
| 6 | .963 | 8.0 | 65.7 | | | | | | |
| 7 | .866 | 7.2 | 73.0 | | | | | | |
| 8 | .780 | 6.5 | 79.1 | | | | | | |
| 9 | .751 | 6.3 | 85.7 | | | | | | |
| 10 | .713 | 5.9 | 91.6 | | | | | | |
| 11 | .527 | 4.4 | 96.0 | | | | | | |
| 12 | .475 | 4.00 | 100.000 | | | | | | |

**Table 5.17** The items and statements that measure the Openness (O) domain.

| Item no.* | Statement |
|---|---|
| **8** | Once I find the right way to do something, I stick to it. |
| **18** | I believe letting students hear controversial speakers can only confuse and mislead them. |
| **38** | I believe we should look to our religious authorities for decisions on moral issues. |

* reprinted with permission of the Psychological Assessment Resources, Inc.

**Table 5.18** Rotated component matrix - Results from a factor analysis of the personality data.

| | Component | | | | |
|---|---|---|---|---|---|
| Item | 1 | 2 | 3 | 4 | 5 |
| 38 | .721 | | | -.224 | -.162 |
| 18 | .661 | -.229 | .175 | | .314 |
| 8 | .599 | | | .142 | -.117 |
| 48 | -.130 | -.745 | .258 | -.166 | .149 |
| 13 | -.148 | .644 | .409 | | .137 |
| 53 | -.243 | .544 | .149 | -.337 | .143 |
| 43 | | | .799 | -.214 | -.152 |
| 23 | | | .627 | .226 | |
| 3 | | | | .754 | |
| 33 | .416 | .238 | | .503 | |
| 28 | | .131 | -.103 | -.320 | .727 |
| 58 | -.157 | | | .201 | .706 |

**Table 5.19** Cronbach alphas for factor items.

| Items | Alpha if item deleted |
|---|---|
| 38 | .33 |
| 18 | .41 |
| 8 | .42 |

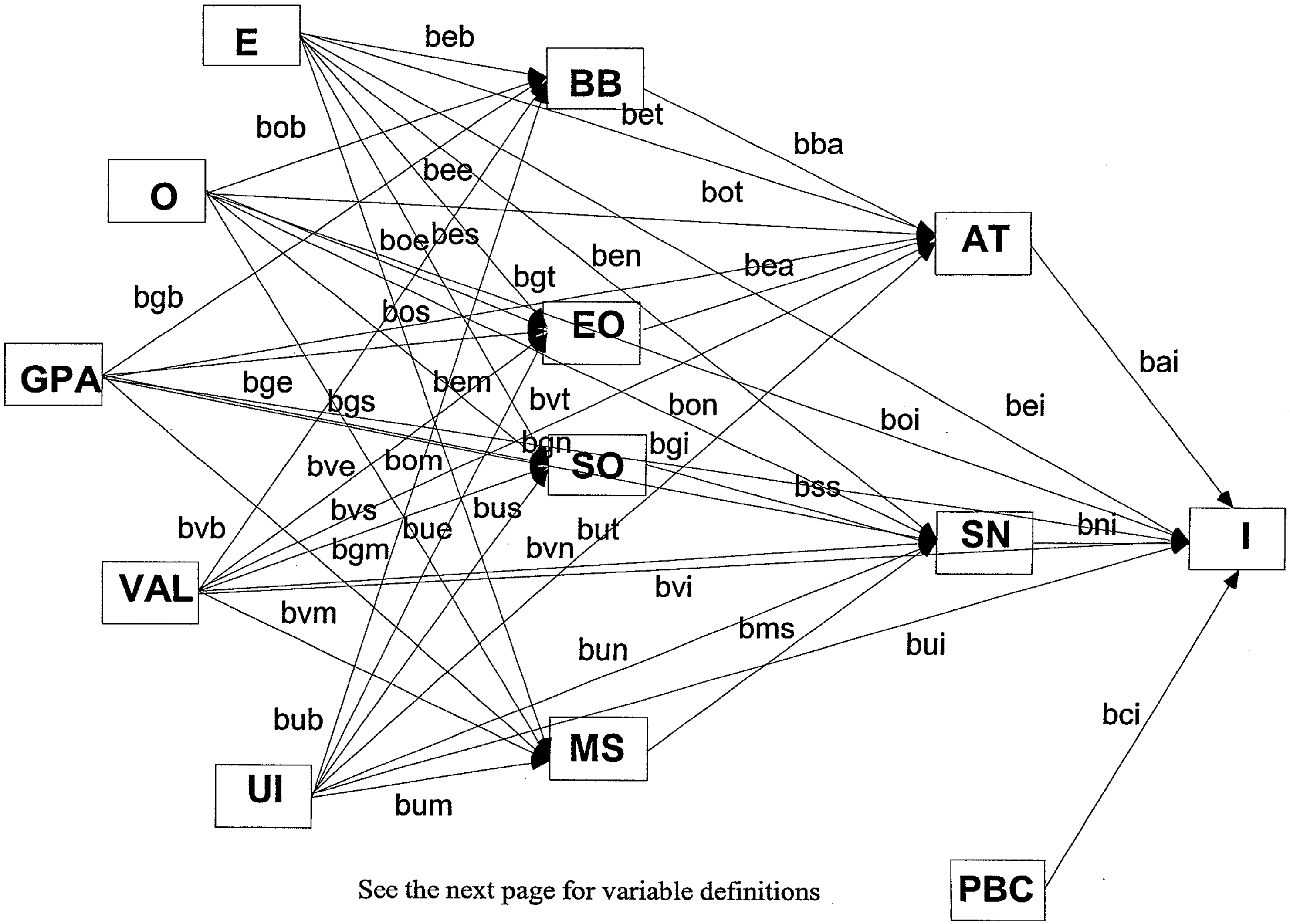
### 5.6.3 Model Analysis

The structural equation model of extensions agents' attitudes towards the use of POSOP is depicted in Figure 5.4. The extension agents' intention to use POSOP (I) is a function of three basic determinants. The first is their attitude towards the use of POSOP (AT), the second reflects their perception of generalised significant others' pressures put on them to use POSOP (or their subjective norm (SN)), and the third is their perception of difficulty in using POSOP (PBC).

Just as intention is assumed to have determinants, extension agents' attitudes (AT) are also a function of their beliefs with regard to using POSOP (BB) and of their views on the outcomes from using POSOP (EO). Likewise, the subjective norm (SN) is a function of the beliefs underlying their beliefs with regard to specific significant others expecting them to use POSOP (SO) and also the motivation to comply with their significant others (MS).

Five external variables, attitudes towards POSOP' s value as a decision support tool (VAL), and its user interface (UI), Openness (O), Extraversion (E), and grade point average (GPA) were included in the model.

**Figure 5.4** The structural equation model of extension agents' attitudes towards the use of POSOP




See the next page for variable definitions

**Figure 5.4** Variable Definitions (cont.)

| | |
|---|---|
| **I**: | Intention to use POSOP. |
| **AT**: | Attitudes towards the use of POSOP. |
| **SN**: | Perception of generalized significant others' pressure on using POSOP. |
| **PBC**: | Perception of difficulty in using POSOP. |
| **BB**: | Beliefs with regard to using POSOP. |
| **EO**: | Views on expected outcomes from using POSOP. |
| **SO**: | Beliefs with regard to specific significant others expecting them to use POSOP. |
| **MS**: | Motivation to comply with their specific significant others. |
| **O**: | Openness |
| **E**: | Extraversion |
| **GPA**: | Grade point average of the extension agents at a certificate level. |
| **VAL**: | attitudes towards POSOP' s value as a decision support tool. |
| **UI**: | attitudes towards POSOP' s user interface. |

| | | | | |
|---|---|---|---|---|
| **beb:** | E | → | BB | regression weight. |
| **bee:** | E | → | EO | regression weight. |
| **bes:** | E | → | SO | regression weight. |
| **bem:** | E | → | MS | regression weight. |
| **bob:** | O | → | BB | regression weight. |
| **boe:** | O | → | EO | regression weight. |
| **bos:** | O | → | SO | regression weight. |
| **bom:** | O | → | MS | regression weight. |
| **bgb:** | GPA | → | BB | regression weight. |
| **bge:** | GPA | → | EO | regression weight. |
| **bgs:** | GPA | → | SO | regression weight. |
| **bgm:** | GPA | → | MS | regression weight. |
| **bvb:** | VAL | → | BB | regression weight. |
| **bve:** | VAL | → | EO | regression weight. |
| **bvs:** | VAL | → | SO | regression weight. |
| **bvm:** | VAL | → | MS | regression weight. |

**Figure 5.4** Variable Definitions (cont.)

| | | | | |
|---|---|---|---|---|
| **bub:** | UI | → | BB | regression weight. |
| **bue:** | UI | → | EO | regression weight. |
| **bus:** | UI | → | SO | regression weight. |
| **bum:** | UI | → | MS | regression weight. |
| **bea:** | EO | → | AT | regression weight. |
| **bss:** | SO | → | SN | regression weight. |
| **bms:** | MS | → | SN | regression weight. |
| **bba:** | BB | → | AT | regression weight. |
| **bet:** | E | → | AT | regression weight. |
| **ben:** | E | → | SN | regression weight. |
| **bot:** | O | → | AT | regression weight. |
| **bon:** | O | → | SN | regression weight. |
| **bgt:** | GPA | → | AT | regression weight. |
| **bgn:** | GPA | → | SN | regression weight. |
| **bvt:** | VAL | → | AT | regression weight. |
| **bvn:** | VAL | → | SN | regression weight. |
| **but:** | UI | → | AT | regression weight. |
| **bun:** | UI | → | SN | regression weight. |
| **bci:** | B4 | → | I | regression weight. |
| **bai:** | A12 | → | I | regression weight. |
| **bni:** | SN | → | I | regression weight. |
| **bei:** | E | → | I | regression weight. |
| **boi:** | O | → | I | regression weight. |
| **bgi:** | GPA | → | I | regression weight. |
| **bvi:** | VAL | → | I | regression weight. |
| **bui:** | UI | → | I | regression weight. |

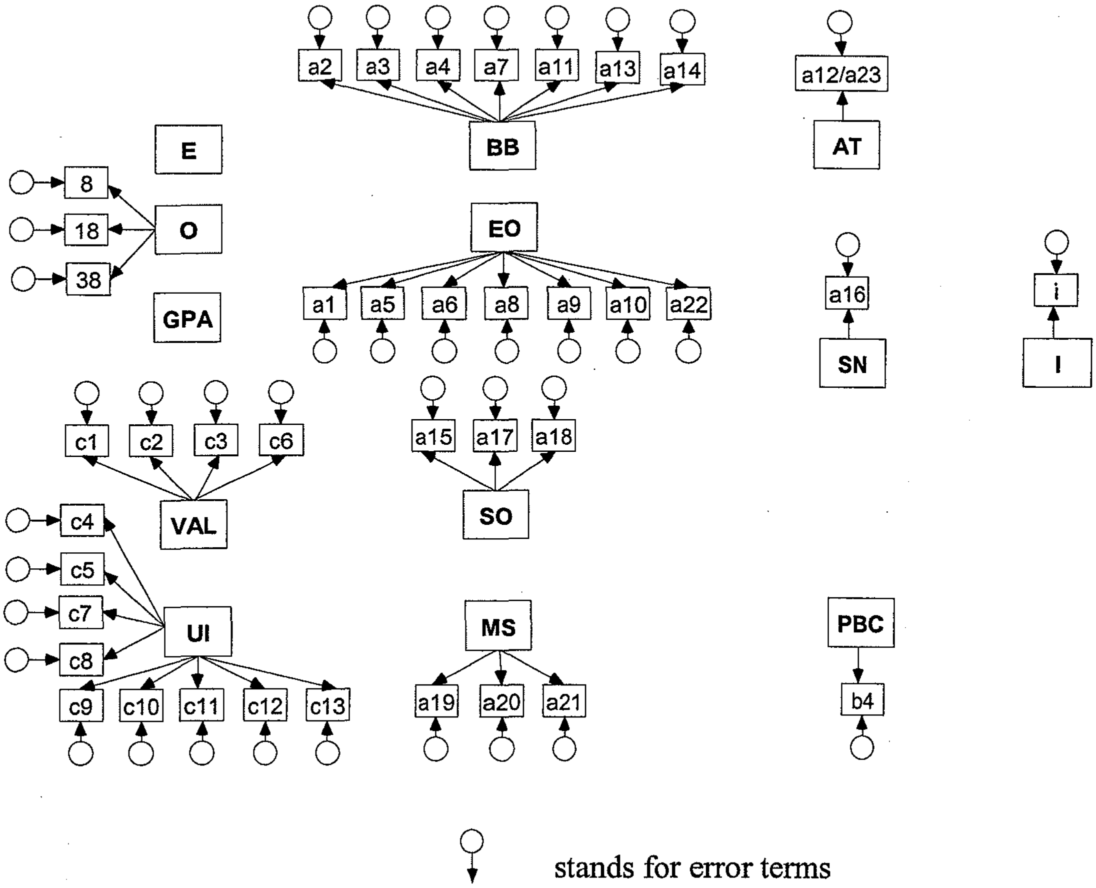
The structural equation model was converted into a set of structural equations as follows.

| **Endogenous Variable** = | **Exogenous Variables** | = **Endogenous variables** | **Error** |
|---|---|---|---|
| | O, E, GPA, VAL, UI, PBC | AT, SN, BB, EO, SO, MS | $+\varepsilon_i$ |
| BB | $b_{ob}O + b_{eb}E + b_{gb}GPA + b_{vb}VAL + b_{ub}UI$ | | $+\varepsilon_1$ |
| EO | $b_{oe}O + b_{ee}E + b_{ge}GPA + b_{ve}VAL + b_{ue}UI$ | | $+\varepsilon_2$ |
| SO | $b_{os}O + b_{es}E + b_{gs}GPA + b_{vs}VAL + b_{us}UI$ | | $+\varepsilon_3$ |
| MS | $b_{om}O + b_{em}E + b_{gm}GPA + b_{vm}VAL + b_{um}UI$ | | $+\varepsilon_4$ |
| AT | $b_{ot}O + b_{et}E + b_{gt}GPA + b_{vt}VAL + b_{ut}UI$ | $b_{ba}BB + b_{ea}EO$ | $+\varepsilon_5$ |
| SN | $b_{on}O + b_{en}E + b_{gn}GPA + b_{vn}VAL + b_{un}UI$ | $b_{ss}SO + b_{ms}MS$ | $+\varepsilon_6$ |
| I | $b_{oi}O + b_{ei}E + b_{gi}GPA + b_{vi}VAL + b_{ui}UI$ $b_{ci}PBC+$ | $b_{ai}AT + b_{ni}SN$ | $+\varepsilon_7$ |

#### 5.6.3.1. Analysis Approach

According to Hair et al. (1998), there are two analysis approaches for structural equation modelling – a single-step and a two-step. When the model has both strong theoretical rationale and a highly reliable measure, a single-step analysis should be the best approach as it simultaneously estimates both structural and measurement models which yields a more accurate relationship and reduces the possible 'structure-measurement' interaction. However, when the model is only tentative and the measures are less reliable, a two-step analysis should be used. In two-step analysis the measurement model is estimated first, and then the structural model is estimated fixing measurement model in this stage. The rationale behind this approach is to avoid the possible interaction of the measurement and structural models. It yields an accurate representation of the indicators which can be best achieved in two stages. As the proposed theory was only tentative, and the measures were somewhat less reliable, a two-step approach was used in this analysis. The measurement models are depicted in Figure 5.5.

**Figure 5.5** The measurement model of extension agents' attitudes towards the use of POSOP.




**Variable Definitions:**

See Appendix E, Section A Attitudes towards use of POSOP for a1 - a23 (given as A1 to A23).

See Appendix E, Section B Knowledge and skills for b4 (given as B4).

See Appendix E, Section C Attitudes towards POSOP's features for c1 - c13 (given as C1 to C13)

See figure 5.3 for I, AT, SN, PBC, BB, EO, SO, MS, E, O, GPA, VAL, and UI.

All variables in the structural model were tested for homogeneity of variances. The variances of all variables except I were homogeneous (Table 5.20). The heterogeneous variance in I might affect goodness-of-fit of the model.

**Table 5.20** Test of homogeneity of variances

| Variables | Levene Statistic | df1 | df2 | Sig. |
|---|---|---|---|---|
| I | 5.785 | 1 | 128 | .018 |
| A12 | .895 | 1 | 128 | .346 |
| A23 | 3.862 | 1 | 128 | .052 |
| SN | .083 | 1 | 128 | .774 |
| PBC | .555 | 1 | 128 | .458 |
| BB | .307 | 1 | 128 | .580 |
| EO | .134 | 1 | 128 | .715 |
| SO | 3.542 | 1 | 128 | .062 |
| MS | 2.625 | 1 | 128 | .108 |
| VAL | 3.500 | 1 | 128 | .064 |
| UI | 3.183 | 1 | 128 | .077 |
| E | .830 | 1 | 128 | .364 |
| O | .540 | 1 | 128 | .464 |
| GPA | .467 | 1 | 128 | .496 |

Notes: A12 = extension agents' perceived usefulness of POSOP.
A23 = extension agents' attitude towards the use of POSOP.
dfl = degree of freedom for between groups (the workshop and mail survey).
df2 = degree of freedom for within groups.

#### 5.6.3.2 Input Data

Unlike other multivariate data analyses, structural equation modelling only uses either the variance-covariance, or the correlation matrix, as its input data. When testing a series of causal relationships, co-variances are the preferred input matrix (Hair et al., 1998). In the proposed study, correlations were used for both practical and theoretical reasons. From a practical perspective, correlations are more easily interpreted, and the diagnosis of the results is more direct. From a theoretical perspective, the proposed study attempts to examine the pattern of relationships among the determinants of extension agents' intention to use POSOP. For these reasons, the correlation matrix was deemed preferable.

The Pearson product-moment correlation coefficients of all variables included in the model were computed using SPSS, and then the correlation matrix was used as input data for the structural equation modelling in Amos (Arbuckle and Wonthe, 1999). Maximum likelihood was used as it is generally accepted that the minimum sample size for efficient and reliable maximum likelihood estimates is 100 to 150. When the sample size increases above this value, the maximum likelihood estimates increase in sensitivity, with data differences. As the sample size becomes large (400 to 500), the method becomes too sensitive and almost any difference is detected and gives rise to illogical low goodness-of-fit measures (Hair et al., 1998). Using maximum likelihood, the extension agents' attitude towards the use of POSOP was studied using two aspects – extension agents' perceived usefulness of POSOP, and extension agents' attitude towards the use of POSOP as a decision support tool.

## 5.7 Summary

As the objectives of this research were to explain the agents' psychological processes underlying the use of POSOP, the acceptance process unfolds once the agents' beliefs that underlie their attitude, subjective norm, and perceived behavioural control are traced. It is proposed that a structural equation model which provides a holistic view of a series of simultaneously causal relationships is more appropriate than the expectancy-value model.

The agents were middle-aged and experienced. Most were trained in plant science and technology at certificate level, and in agricultural extension at the bachelor degree level. None of them was trained in plant pathology at any education level. As might be expected, their attitudes towards POSOP' s value as a decision support tool and its user interface were positive. The agents' intentions to use POSOP were strong. Their attitudes towards its use were positive, as were their subjective norm. Their perception of generalised control over using POSOP (PBC) was high. In general, they were in favour of using POSOP, and believed a wide range of well-prepared expert systems had a potential to help them with their decision support work. They agreed that the development of many more expert systems should be provided.

The personality tests were found to be normal, and their intelligence, in terms of, GPA was average.

Two structural equation models – the agents' perceived usefulness of POSOP, and the agents' attitude towards the use of POSOP were proposed. The model analysis approach and input data were also discussed. A software package of structural equation model, Amos 4.0, was used in the model analysis.

The results and discussion of the two models are presented in the next chapter.

# CHAPTER 6

# Results and Discussion

## 6.1 Introduction

Chapter five contains a discussion on the desirability of developing a structural equation model of extension agents' attitudes towards the use of POSOP (Figure 5.3). In fact, two structural equation models – the agents' perceived usefulness of POSOP (ATU), and their attitude towards the use of POSOP (ATP) were developed, evaluated, modified, and interpreted. The results of this analysis are reported and discussed in this chapter. For the development of useful extension tools that will in reality be used, it is vital to fully understand which factors determine the extension officers' views towards expert systems and how these factors interact to ensure widespread adoption and use. This is the significant contribution to knowledge that this research provides.

The value of the two models was assessed using three types of goodness-of-fit (GOF) measures: absolute fit, incremental fit, and parsimonious fit. Generally, GOF indices range from 0 to 1, where 1 indicates a perfect fit. The criteria used for each type of GOF measure (Arbuckle and Wonthe, 1999; Hair et al., 1998) were as follows:

(1) For the absolute GOF measures: a low likelihood chi-square ($\chi^2$) value with high degrees of freedom and a p value $> 0.05$, a high goodness-of-fit index (GFI) (there is no established threshold; a higher value indicates a better fit), and a root mean square error of approximation (RMSEA) value of $< 0.10$.

(2) For the incremental GOF measures, an adjusted GOF index (AGFI), an incremental fit index (IFI), and a comparative fit index (CFI) values all $\geq 0.90$ are considered acceptable.

(3) For the parsimonious GOF measures, a normed chi-square ($\chi^2$), or a chi-square ($\chi^2$) to degrees of freedom ratio, with the reasonable threshold of 5 to 1, or the acceptable fit ranges of 2 or 3 to 1; a parsimonious GOF index (PGFI), and a

parsimonious comparative fit index (PCFI) value of equal to, or greater than that of the null model.

## 6.2 A Model of the Extension Agents' Perceived Usefulness of POSOP (ATU)

### 6.2.1 Goodness-of-Fit Measures

Each of the three types of GOF measures for the estimated, saturated, and null models are given in Table 6.1.

**Table 6.1** GOF measures for the estimated, saturated, and null models (ATU).

| GOF Measure | Estimated | Saturated | Null |
|---|---|---|---|
| **Absolute Fit** | | | |
| Likelihood-ratio chi-square ($\chi^2$) | 144.877 | 0.000 | 380.650 |
| Degrees of freedom (df) | 36 | 0 | 78 |
| P | 0.000 | | 0.000 |
| Number of parameters | 55 | 91 | 13 |
| Goodness-of-fit index (GFI) | 0.849 | 1.000 | 0.597 |
| Root mean square error of approximation (RMSEA) | 0.153 | | 0.173 |
| **Incremental Fit** | | | |
| Adjusted GFI (AGFI) | 0.618 | | 0.530 |
| Incremental fit index (IFI) | 0.684 | 1.000 | 0.000 |
| Comparative fit index (CFI) | 0.640 | 1.000 | 0.000 |
| **Parsimonious Fit** | | | |
| Normed chi-square (normed $\chi^2$) | 4.024 | | 4.880 |
| Parsimonious GFI (PGFI) | 0.336 | | 0.512 |
| Parsimonious CFI (PCFI) | 0.296 | 0.000 | 0.000 |

### Absolute GOF Measures

The likelihood-ratio chi-square ($\chi^2$) value of 144.877 with 36 degrees of freedom was statistically significant with a p value of <0.001, indicating that a significant difference between the observed and predicted correlations existed. This might be due to the mixed data from the mail survey and the workshop. The GFI value, of 0.849, fell slightly below the desired threshold of 0.900. The RMSEA had a value of 0.153 which was outside the acceptable fit range of < 0.10. All these suggested the estimated model could be improved.

### Incremental GOF Measures

The model was evaluated in comparison to a baseline or null model. The null model had a chi-square ($\chi^2$) value of 380.650 with 78 degrees of freedom. Although there was a substantial reduction in the chi-square value due to the estimated coefficients in the model, all incremental GOF measures (ranging from 0.684 to 0.618) fell considerably below the desired threshold of 0.900, indicating that the model could be improved if the appropriate parameters were included.

### Parsimonious GOF Measures

The normed chi-square ($\chi^2$), or chi-square ($\chi^2$) to degrees of freedom ratio, of 4.024 fell within the reasonable threshold of 5 to 1, but outside the acceptable fit ranges of 2 or 3 to 1. The PGFI of the estimated model had a smaller value (0.336) than that of the null model (0.512). All these indicated a non-parsimonious model and suggested the model could be improved if the redundant parameters were dropped from the model. The PCFI was examined later, when making comparisons between the models.

In summary, each type of GOF measure indicated the inefficiency of the estimated model, and suggested that dropping redundant parameters and, following a reconsideration of the logic of the model, including more appropriate parameters, would improve the model.

### 6.2.2 Modifying the Model

The standardised parameter estimates for the estimated model are given in Table 6.2. The relationships with p values of > 0.050, being considered less important in explaining the model, were dropped. Note that one parameter labeled 'bni' with a p value of 0.336 was kept in the model as it was a core parameter in the TPB, and similarly, the other parameter labeled 'but' with a p value of 0.062 was also kept for its potential to explain the influence of the user interface on the agents' perceived usefulness of POSOP.

**Table 6.2** Standardised parameter estimates for the estimated model (ATU).

| | **Regression weight** | | **Standardised parameter Estimate** | **p** | **Label** |
|---|---|---|---|---|---|
| VAL | → | EO | 0.402 | 0.000 | bve |
| MS | → | SN | 0.381 | 0.000 | bms |
| VAL | → | BB | 0.370 | 0.000 | bvb |
| EO | → | AT | 0.352 | 0.000 | bea |
| BB | → | AT | 0.327 | 0.000 | bba |
| VAL | → | I | 0.305 | 0.001 | bvi |
| VAL | → | SO | 0.261 | 0.007 | bvs |
| AT | → | I | 0.219 | 0.007 | bai |
| PBC | → | I | -0.186 | 0.018 | bci |
| UI | → | SO | 0.216 | 0.024 | bus |
| O | → | SO | -0.183 | 0.027 | bos |
| SO | → | SN | 0.184 | 0.043 | bss |
| UI | → | AT | 0.158 | 0.062 | but |
| UI | → | MS | 0.153 | 0.134 | bum |
| E | → | I | -0.116 | 0.140 | bei |
| GPA | → | AT | -0.089 | 0.214 | bgt |
| O | → | MS | -0.109 | 0.215 | bom |
| O | → | AT | -0.087 | 0.235 | bot |
| GPA | → | SN | -0.082 | 0.293 | bgn |

**Table 6.2** Standardised parameter estimates for the estimated model (ATU) (cont.).

| | Regression weight | | Standardised parameter Estimate | P | Label |
|---|---|---|---|---|---|
| O | → | SN | -0.082 | 0.309 | bon |
| SN | → | I | -0.076 | 0.336 | bni |
| GPA | → | MS | -0.079 | 0.362 | bgm |
| E | → | EO | 0.071 | 0.382 | bee |
| E | → | BB | 0.064 | 0.435 | beb |
| O | → | I | -0.057 | 0.470 | boi |
| GPA | → | BB | 0.057 | 0.483 | bgb |
| UI | → | BB | 0.066 | 0.490 | bub |
| UI | → | SN | 0.060 | 0.518 | bun |
| O | → | BB | 0.051 | 0.536 | bob |
| VAL | → | AT | 0.055 | 0.549 | bvt |
| E | → | SN | -0.042 | 0.596 | ben |
| E | → | AT | -0.038 | 0.597 | bet |
| VAL | → | SN | -0.049 | 0.603 | bvn |
| E | → | MS | -0.042 | 0.628 | bem |
| E | → | SO | 0.039 | 0.634 | bes |
| GPA | → | SO | 0.037 | 0.646 | bgs |
| GPA | → | I | -0.031 | 0.693 | bgi |
| GPA | → | EO | -0.027 | 0.737 | bge |
| UI | → | I | 0.064 | 0.751 | bui |
| VAL | → | MS | -0.023 | 0.824 | bvm |
| UI | → | EO | 0.019 | 0.841 | bue |
| O | → | EO | -0.004 | 0.966 | boe |

The modification indices (which are calculated for each non-estimated relationship) for the estimated model, after dropping the redundant parameters, are given in Table 6.3. The modification index value corresponds approximately to the decrease in the chi-square value that would occur if the parameter was estimated. The largest modification index was 35.353, indicating that allowing VAL and UI to correlate would decrease the chi-square value by at least 35.353. Two modification indices of interest were the correlations between VAL and UI, and between VAL and O. It is sensible that POSOP' s user interface (UI) should be related to its value as a decision support tool (VAL), and this value might be associated with the openness (O) domain. Consequently, these two parameters, VAL ←→ UI and VAL ←→ O, were included in the model. The modified model is presented in Figure 6.1.

**Table 6.3** Modification indices for the estimated model (ATU) after dropping the redundant parameters[1].

| Covariances | | | Modification[2] Indices | Parameter[3] Change |
|---|---|---|---|---|
| VAL | ←→ | UI | 35.353 | 0.093 |
| eeo | ←→ | ebb | 25.737 | 0.050 |
| eso | ←→ | ems | 18.627 | 0.126 |
| eeo | ←→ | eso | 16.119 | 0.058 |
| eeo | ←→ | ems | 14.749 | 0.058 |
| PBC | ←→ | ebb | 5.855 | -0.078 |
| PBC | ←→ | eeo | 5.854 | -0.059 |
| O | ←→ | VAL | 4.163 | -0.062 |

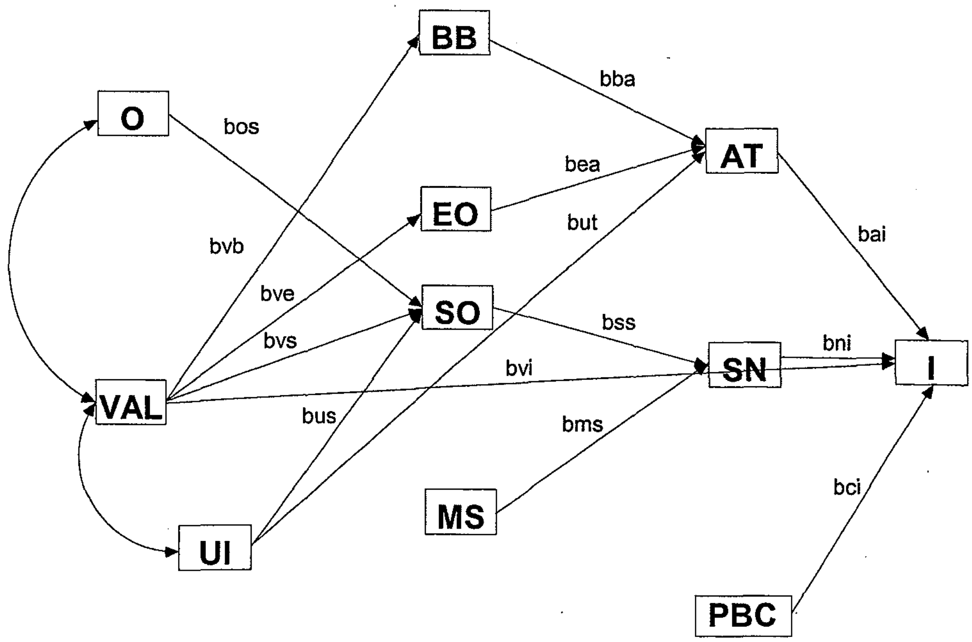
[1] Error terms were not shown in the path diagram.

[2] Only modification indices greater than 4.0 are shown.

[3] Approximate estimates of how much the parameter would change if they were estimated.

←→ stand for covariances.

**Figure 6.1** The modified model of the extension agents' perceived usefulness of POSOP (ATU) – The input model.




E and GPA were not shown in the model.

The GOF measures for the estimated, modified, saturated, and null models are given in Table 6.4.

**Table 6.4** GOF measures for the estimated, modified, saturated, and null models (ATU).

| GOF Measure | Estimated | Modified | Saturated | Null |
|---|---|---|---|---|
| **Absolute Fit** | | | | |
| Likelihood-ratio chi-square ($\chi^2$) | 144.877 | 118.893 | 0.000 | 380.650 |
| Degrees of freedom (df) | 36 | 62 | 0 | 78 |
| P | 0.000 | 0.000 | | 0.000 |
| Number of parameters | 55 | 29 | 91 | 13 |
| Goodness-of-fit index (GFI) | 0.849 | 0.869 | 1.000 | 0.597 |
| Root mean square error of approximation (RMSEA) | 0.153 | 0.084 | | 0.173 |
| **Incremental Fit** | | | | |
| Adjusted GFI (AGFI) | 0.618 | 0.808 | | 0.530 |
| Incremental fit index (IFI) | 0.684 | 0.821 | 1.000 | 0.000 |
| Comparative fit index (CFI) | 0.640 | 0.812 | 1.000 | 0.000 |
| **Parsimonious Fit** | | | | |
| Normed chi-square (normed $\chi^2$) | 4.024 | 1.918 | | 4.880 |
| Parsimonious GFI (PGFI) | 0.336 | 0.592 | | 0.514 |
| Parsimonious CFI (PCFI) | 0.296 | 0.645 | 0.000 | 0.000 |

**Absolute GOF Measures**

The likelihood-ratio chi-square ($\chi^2$) of the modified model value of 118.893 with 62 degrees of freedom was statistically significant with a p value of $<0.001$, indicating that a significant difference between the observed and predicted correlations still remained. The GFI value, of 0.869, fell slightly below the desired threshold of 0.900; and the RMSEA value, of 0.084, fell within the acceptable fit of $< 0.10$. The modified model was deemed acceptable.

**Incremental GOF Measures**

All the incremental GOF measures (AGFI, IFI, and CFI) for the modified model were below the desired threshold of 0.900 with the figures of 0.808, 0.821, and 0.812 respectively. However, when compared with the estimated model, all the indices improved considerably. All these indicated a better fitting model.

**Parsimonious GOF Measures**

The normed chi-square ($\chi^2$) value of 1.918 fell within the acceptable fit range of 2 to 1; the PGFI value, of 0.592, was greater than those of the null (0.514), and estimated (0.336) models; and the PCFI value, of 0.645, was greater than that of the estimated model (0.296). All these indicated a more parsimonious model.

In summary, each type of GOF measures indicated that the modified model was a more parsimonious, better fitting, and more acceptable model, despite the small sample size. However, making general inferences to the whole population should be restricted due to the existence of a significant difference between the observed and predicted correlations.

## 6.3 A Model of the Extension Agents' Attitude towards the Use of POSOP (ATP)

### 6.3.1 Goodness-of-Fit Measures

Each of the three types of GOF for the estimated, saturated, and null models are given in Table 6.5.

**Absolute Fit Measures**

The likelihood-ratio chi-square ($\chi^2$) value of 144.345 with 36 degrees of freedom was statistically significant with a p value of $<0.001$, indicating that a significant difference between the observed and predicted correlations existed. The GFI value,

**Table 6.5** GOF measures for the estimated, saturated, and null models (ATP).

| GOF Measure | Estimated | Saturated | Null |
|---|---|---|---|
| **Absolute Fit** | | | |
| Likelihood-ratio chi-square ($\chi^2$) | 144.345 | 0.000 | 399.201 |
| Degrees of freedom (df) | 36 | 0 | 78 |
| P | 0.000 | | 0.000 |
| Number of parameters | 55 | 91 | 13 |
| Goodness-of-fit index (GFI) | 0.850 | 1.000 | 0.618 |
| Root mean square error of approximation (RMSEA) | 0.153 | | 0.179 |
| **Incremental Fit** | | | |
| Adjusted GFI (AGFI) | 0.621 | | 0.555 |
| Incremental fit index (IFI) | 0.702 | 1.000 | 0.000 |
| Comparative fit index (CFI) | 0.663 | 1.000 | 0.000 |
| **Parsimonious Fit** | | | |
| Normed chi-square (normed $\chi^2$) | 4.010 | | 5.118 |
| Parsimonious GFI (PGFI) | 0.336 | | 0.530 |
| Parsimonious CFI (PCFI) | 0.306 | 0.000 | 0.000 |

of 0.850, fell slightly below the desired threshold of 0.900. The RMSEA had a value of 0.153 which was outside the acceptable fit of < 0.10. All these suggested the estimated model could be improved.

**Incremental Fit Measures**

The model was evaluated against a baseline or null model. The null model had a chi-square ($\chi^2$) value of 399.201 with 78 degrees of freedom. Although there was a substantial reduction in the chi-square value due to the estimated coefficients in the model, all incremental GOF measures (ranging from 0.702 to 0.621) fell considerably below the desired threshold of 0.900, indicating that the model could potentially be improved if the appropriate parameters were included.

**Parsimonious Fit Measures**

The normed chi-square ($\chi^2$) or chi-square ($\chi^2$) to degrees of freedom ratio of 4.010 fell within the reasonable threshold of 5 to 1, but outside the acceptable fit ranges of 2 to 1 or 3 to 1. The PGFI of the estimated model had a smaller value (0.336) than that of the null model (0.530). All these indicated a non-parsimonious model and similarly suggested the model could be improved if the redundant parameters were dropped. The PCFI was examined later, when making comparisons between the models.

In summary, each type of GOF measure indicated the inefficiency of the estimated model, and suggested that dropping the redundant parameters and including rather more logically appropriate parameters would improve the model.

### 6.3.2 Modifying the Model

As before, the parameter estimates for the estimated model are given in Table 6.6. Those relationships with p values of > 0.050 that were not considered logically important in explaining the model were dropped. Note that three parameters, labeled 'bba,' 'bea,' and 'bni,' with p values of 0.413, 0.319, and 0.518 respectively, were kept in the model as they were core parameters in the TPB.

The modification indices for the estimate model, after dropping the redundant parameters, are given in Table 6.3. Two modification indices of particular interest, VAL $\leftrightarrow$ UI and VAL $\leftrightarrow$ O, were included in the model. The modified model is presented in Figure 6.2

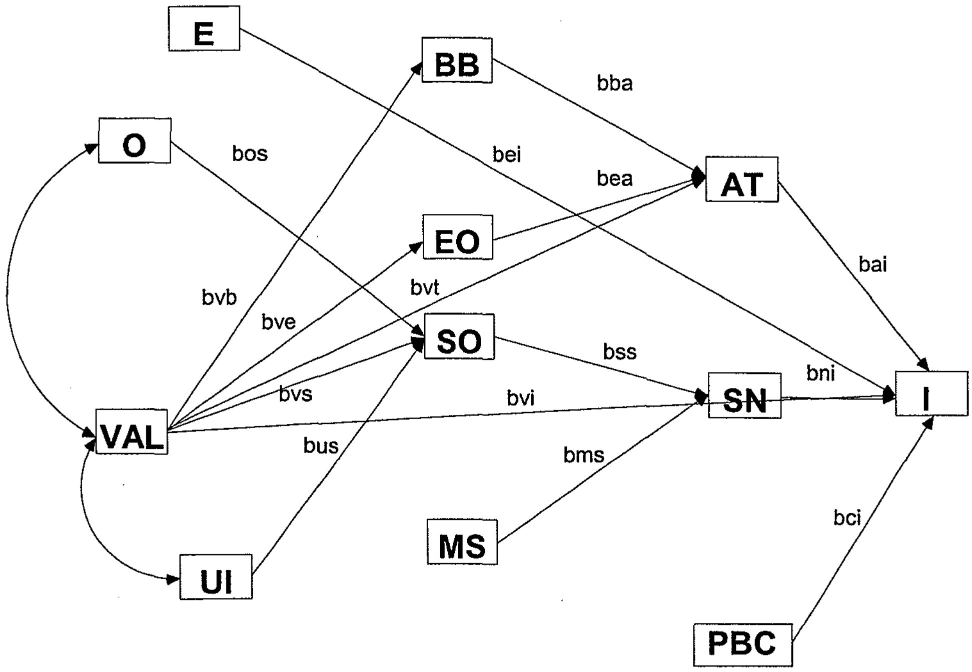
**Table 6.6** Standardised parameter estimates of the estimated model (ATP).

| | Regression weight | | Standardised parameter estimate | p | Label |
|---|---|---|---|---|---|
| AT | → | I | 0.641 | 0.000 | bai |
| VAL | → | EO | 0.402 | 0.000 | bve |
| MS | → | SN | 0.381 | 0.000 | bms |
| VAL | → | BB | 0.370 | 0.000 | bvb |
| VAL | → | AT | 0.310 | 0.003 | bvt |
| VAL | → | SO | 0.261 | 0.007 | bvs |
| PBC | → | I | -0.162 | 0.008 | bci |
| E | → | I | -0.142 | 0.020 | bei |
| UI | → | SO | 0.216 | 0.024 | bus |
| O | → | SO | -0.183 | 0.027 | bos |
| SO | → | SN | 0.184 | 0.043 | bss |
| VAL | → | I | 0.133 | 0.077 | bvi |
| UI | → | MS | 0.153 | 0.134 | bum |
| O | → | MS | -0.109 | 0.215 | bom |
| GPA | → | SN | -0.082 | 0.293 | bgn |
| O | → | SN | -0.082 | 0.309 | bon |
| EO | → | AT | 0.098 | 0.319 | bea |
| GPA | → | MS | -0.079 | 0.362 | bgm |
| GPA | → | AT | -0.072 | 0.373 | bgt |
| E | → | EO | 0.071 | 0.382 | bee |
| O | → | I | -0.054 | 0.384 | boi |
| BB | → | AT | 0.080 | 0.413 | bba |
| E | → | BB | 0.064 | 0.435 | beb |
| GPA | → | BB | 0.057 | 0.483 | bgb |
| UI | → | BB | 0.066 | 0.490 | bub |
| UI | → | SN | 0.060 | 0.518 | bun |
| SN | → | I | -0.039 | 0.518 | bni |
| O | → | BB | 0.051 | 0.536 | bob |

**Table 6.6** Standardised parameter estimates of the estimated model (ATP) (cont.)

| | Regression weight | | Standardised parameter estimate | p | Label |
|---|---|---|---|---|---|
| E | → | SN | -0.042 | 0.596 | ben |
| VAL | → | SN | -0.049 | 0.603 | bvn |
| E | → | MS | -0.042 | 0.628 | bem |
| E | → | SO | 0.039 | 0.634 | bes |
| E | → | AT | 0.038 | 0.642 | bet |
| GPA | → | SO | 0.037 | 0.646 | bgs |
| GPA | → | EO | -0.027 | 0.737 | bge |
| O | → | AT | -0.025 | 0.758 | bot |
| UI | → | AT | 0.028 | 0.769 | but |
| VAL | → | MS | -0.023 | 0.824 | bvm |
| UI | → | I | -0.015 | 0.835 | bui |
| UI | → | EO | 0.019 | 0.841 | bue |
| GPA | → | I | 0.003 | 0.966 | bgi |
| O | → | EO | -0.004 | 0.966 | boe |

**Figure 6.2** The modified model of extension agents' attitude towards the use of POSOP (ATP) – The input model.




GPA was not shown in the model.

The GOF measures for the estimated, modified, saturated, and null models are given in Table 6.7.

**Absolute GOF Measures**

The likelihood-ratio chi-square ($\chi^2$) of the modified model value of 113.902 with 61 degrees of freedom was statistically significant with a p value of <0.001, indicating that the significant difference between the observed and predicted correlations still remained. The GFI value, of 0.875, fell slightly below the desired threshold of 0.900; and the RMSEA value, of 0.082, fell within the acceptable fit of $< 0.10$. The modified model was deemed acceptable.

**Table 6.7** GOF measures for the estimated, modified, saturated, and null models (ATP).

| GOF Measure | Estimated | Modified | Saturated | Null |
|---|---|---|---|---|
| **Absolute Fit** | | | | |
| Likelihood-ratio chi-square ($\chi^2$) | 144.345 | 113.902 | 0.000 | 399.201 |
| Degrees of freedom (df) | 36 | 61 | 0 | 78 |
| P | 0.000 | 0.000 | | 0.000 |
| Number of parameters | 55 | 30 | 91 | 13 |
| Goodness-of-fit index (GFI) | 0.850 | 0.875 | 1.000 | 0.618 |
| Root mean square error of approximation (RMSEA) | 0.153 | 0.082 | | 0.179 |
| **Incremental Fit** | | | | |
| Adjusted GFI (AGFI) | 0.621 | 0.813 | | 0.555 |
| Incremental fit index (IFI) | 0.702 | 0.844 | 1.000 | 0.000 |
| Comparative fit index (CFI) | 0.663 | 0.835 | 1.000 | 0.000 |
| **Parsimonious Fit** | | | | |
| Normed chi-square (normed $\chi^2$) | 4.010 | 1.867 | | 5.118 |
| Parsimonious GFI (PGFI) | 0.336 | 0.586 | | 0.530 |
| Parsimonious CFI (PCFI) | 0.306 | 0.653 | 0.000 | 0.000 |

**Incremental GOF Measures**

All the incremental GOF measures (AGFI, IFI, and CFI) for the modified model were slightly below the desired threshold of 0.900, with the figures of 0.813, 0.844, and 0.835 respectively. However, when compared with the estimated model, all the indices improved considerably. All these indicated a better fitting model.

**Parsimonious GOF Measures**

The normed chi-square ($\chi^2$) value of 1.867 fell with in the acceptable fit range of 2 to 1; the PGFI value, of 0.586, was greater than those of the null (0.530), and estimated (0.336) models; and the PCFI value, of 0.653, was greater than that of the estimated model (0.306). All these indicated a more parsimonious model.

In summary, each type of GOF measure indicated that the modified model was a more parsimonious, better fitting, and more acceptable model, despite the small sample size. However, as before making strong inferences to the whole population should be restricted due to the existence of the significant difference between the observed and predicted correlations. To create a model of greater robustness will require larger sample sizes.

## 6.4 Interpreting the Models

Given the models, the determinants of extension agents' intention to use POSOP were investigated.

### 6.4.1 A Model of the Extension Agents' Perceived Usefulness of POSOP (ATU)

The standardised parameter estimates for the modified model of extension agents' perceived usefulness of POSOP are given in Table 6.8 and in Figure 6.3.

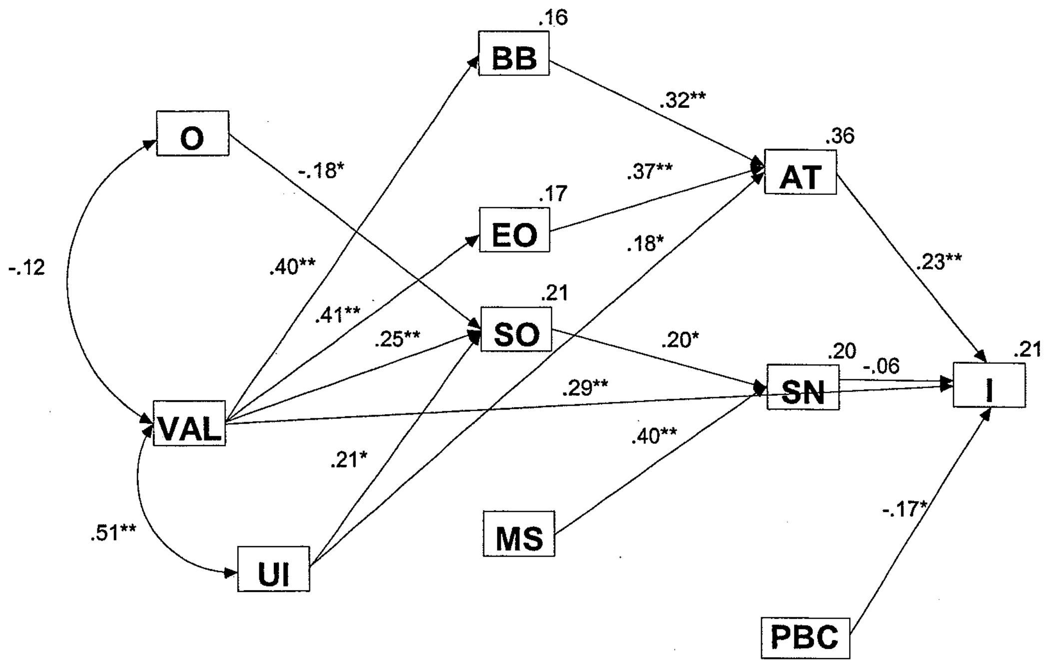
The extension agents' perceived usefulness of POSOP (AT), their subjective norm (SN), perceived behavioural control (PBC), and POSOP's value as a decision support tool (VAL) accounted for 21% of the variance explained by their intention to use POSOP (I). All these variables (AT, PBC, and VAL), except their subjective norm (SN, b = -0.06), directly influenced their intention to use POSOP (I) (b = 0.23, -0.17, and 0.29 respectively). In other words, the more positive their perceived usefulness of POSOP (AT), the less their perception of any difficulty in using POSOP (PBC), and the greater their view of POSOP' s value as a decision support tool (VAL), the stronger their intention to use POSOP.

Their beliefs about (BB), and their evaluation of expected outcomes (EO) from using POSOP directly influenced their perceived usefulness of POSOP (AT) (b = 0.32 and 0.37). In addition, their perceived usefulness of POSOP (AT) was also directly influenced by POSOP' s user interface (UI) (b = 0.18), all these three variables (BB, EO, and UI) accounted for 36% of the variance explained by their perceived usefulness of POSOP (AT).

**Table 6.8** Standardised parameter estimates for the modified model of extension agents' perceived usefulness of POSOP (ATU).

| | Regression Weights | | Standardised parameter estimates | P |
|---|---|---|---|---|
| VAL | → | EO | 0.41 | 0.000 |
| VAL | → | BB | 0.40 | 0.000 |
| MS | → | SN | 0.40 | 0.000 |
| EO | → | AT | 0.37 | 0.000 |
| BB | → | AT | 0.32 | 0.000 |
| VAL | → | I | 0.29 | 0.001 |
| VAL | → | SO | 0.25 | 0.006 |
| AT | → | I | 0.23 | 0.007 |
| UI | → | SO | 0.21 | 0.020 |
| SO | → | SN | 0.20 | 0.019 |
| UI | → | AT | 0.18 | 0.015 |
| SN | → | I | -0.06 | 0.421 |
| PBC | → | I | -0.17 | 0.032 |
| O | → | SO | -0.18 | 0.026 |
| | **Correlations** | | | |
| VAL | ←→ | UI | 0.51 | 0.000 |
| O | ←→ | VAL | -0.12 | 0.126 |

**Figure 6.3** Standardized parameter estimates and squared multiple correlations for the structural model of extension agents' perceived usefulness of POSOP (ATU).




[1] The numbers shown on the single-headed arrow lines give the standardized parameter estimates (b).

[2] The numbers shown on top of rectangles are the squared multiple correlations ($R^2$).

[3] The numbers shown on the double-head arrow lines give the correlation estimates (r).

[4] E and GPA were not shown in the model.

** Significant at the .01 level.

* Significant at the .05 level.

Besides, their perceived usefulness (AT) was not only directly influenced by those three variables (BB, EO, and UI), but also indirectly, and substantially, influenced by POSOP' s value as a decision support tool (VAL) (b= 0.28, Table 6.9) with approximately equal effects via their beliefs (BB), and evaluation of expected outcomes (EO) (b = 0.13 and 0.15, not shown in the Table and in the model). In other words, the more positive their beliefs about (BB), and their evaluation of expected outcomes (EO) from using POSOP, and the better its user interface (UI), the more positive their perceived usefulness of POSOP (AT), and thus the stronger is their intention to use POSOP (I).

Their beliefs about whether specific significant others (farmers, organisation, and peers) expected them to use POSOP (SO), and their motivation to comply with their referents (MS), directly influenced their subjective norm (SN) (b = 0.20 and 0.40), and accounted for 20% of the variance explained by their subjective norm (SN). However, the subjective norm (SN) had little, or no effect, on their intention to use POSOP (I) (b= -0.06).

POSOP's value as a decision support tool (VAL) directly and equally influenced their beliefs about (BB), and their evaluation of expected outcomes (EO) from using POSOP (b = 0.40 and 0.41), and accounted for 16%, and 17% of the variances respectively. In other words, the more POSOP's value as a decision support tool (VAL), the more positive their beliefs about (BB), and their evaluation of expected outcomes (EO), from using POSOP, the more positive their perceived usefulness of POSOP (AT), and their intention to use it (I).

**Table 6.9** Standardised indirect effects of the model of extension agents' perceived usefulness of POSOP (ATU).

| | UI | VAL | GPA | O | E | PBC | BB | MS | SO | EO | SN | AT |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **BB** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **MS** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **SO** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **EO** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **SN** | 0.04 | 0.05 | 0 | -0.04 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **AT** | 0 | 0.28 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **I** | 0.04 | 0.06 | 0 | 0 | 0 | 0 | 0.07 | -0.03 | -0.01 | 0.08 | 0 | 0 |

POSOP's value as a decision support tool (VAL), its user interface (UI), and the openness (O) trait directly influenced their beliefs about specific significant others expecting them to use POSOP (SO) (b = 0.25, 0.21, and -0.18 respectively), and accounted for 21% of variance explained by their specific significant others expecting them to use POSOP (SO). The more POSOP's value as a decision support tool (VAL), the better its user interface (UI), the less 'open' agents (O), the stronger their beliefs about their referents expecting them to use POSOP (SO).

The importance of POSOP's user interface (UI) should not to be underrated. Its user interface (UI) was highly correlated with its value as a decision support tool (VAL) (r = 0.51). This emphasised the importance of the user interface (UI) to its value (VAL) in addition to its direct effect on their perceived usefulness of POSOP (AT) (b = 0.18).

The Extraversion trait (E) and the agents' intelligence as reflected in their GPA, had neither direct nor indirect effects on their intention to use POSOP (I). POSOP's value as a decision support tool (VAL) was not associated with the Openness (O) trait (r = -0.12).

In summary, among the variables external to the TPB, POSOP' s perceived value as a decision support tool (VAL) had substantial effects – both direct and indirect – on extension agents' intention to use POSOP (I). On the other hand, the evaluation of its user interface (UI) had no direct effect on their intention to use it; however, it had an indirect effect via their perceived usefulness of POSOP (AT) and contributed to its value as a decision support tool. Their intelligence, in terms of their GPA, their Extraversion (E), and Openness (O) traits had little, or no effect on their intention to use POSOP (I). This was not expected; the Openness (O) trait was not associated with its value as a decision support tool (VAL).

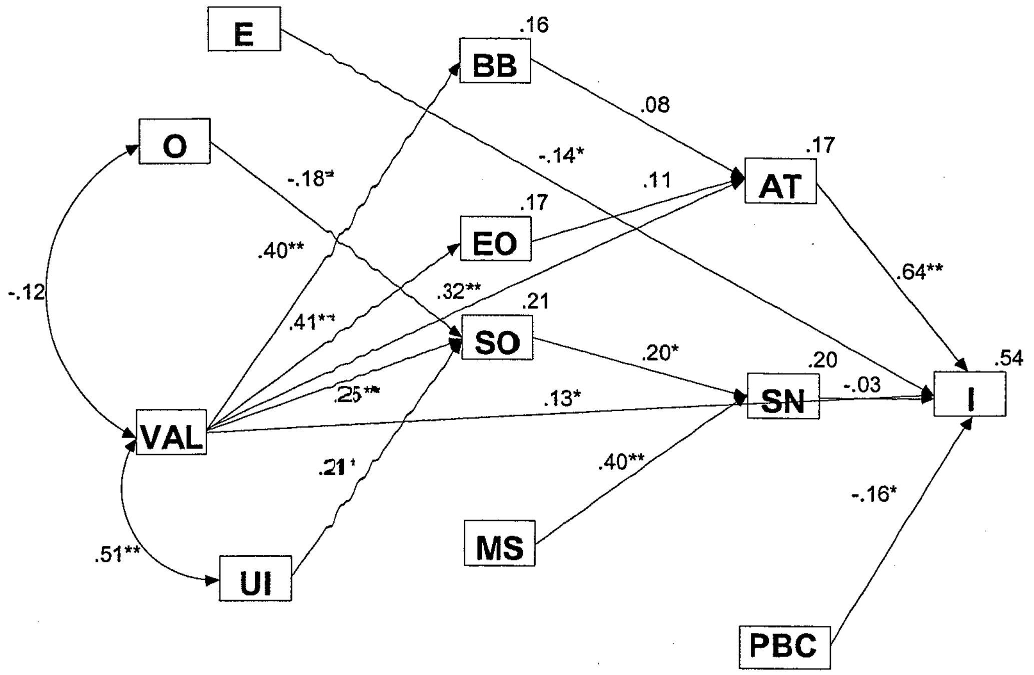
### 6.4.2 A Model of Extension Agents' Attitude towards the Use of POSOP (ATP)

The standardised parameter estimates for the modified model of extension agents' attitude towards the use of POSOP are given in Table 6.10 and in Figure 6.4.

**Table 6.10** Standardised parameter estimates for the modified model of extension agents' attitude towards the use of POSOP (ATP).

| | **Regression Weights** | | **Standardised parameter estimates** | **P** |
|---|---|---|---|---|
| AT | → | I | 0.64 | 0.000 |
| VAL | → | EO | 0.41 | 0.000 |
| VAL | → | BB | 0.40 | 0.000 |
| MS | → | SN | 0.40 | 0.000 |
| VAL | → | AT | 0.32 | 0.000 |
| VAL | → | SO | 0.25 | 0.006 |
| UI | → | SO | 0.21 | 0.020 |
| SO | → | SN | 0.20 | 0.019 |
| VAL | → | I | 0.13 | 0.041 |
| EO | → | AT | 0.11 | 0.277 |
| BB | → | AT | 0.08 | 0.441 |
| SN | → | I | -0.03 | 0.576 |
| E | → | I | -0.14 | 0.018 |
| PBC | → | I | -0.16 | 0.008 |
| O | → | SO | -0.18 | 0.026 |
| | **Correlations** | | | |
| VAL | ←→ | UI | 0.51 | 0.000 |
| O | ←→ | VAL | -0.12 | 0.126 |

**Figure 6.4** Standardized parameter estimates and squared multiple correlations for the structural model of extension agents' attitude towards the use of POSOP (ATP).




[1] The numbers shown on the single-headed arrow lines give the standardized parameter estimates (b).

[2] The numbers shown on top of rectangles are the squared multiple correlations ($R^2$).

[3] The numbers shown on the double-head arrow lines give the correlation estimates (r).

[4] GPA was not shown in the model.

** Significant at the .01 level

* Significant at the .05 level

Extension agents' attitude towards the use of POSOP (AT), subjective norm (SN), perceived behavioural control (PBC), extraversion (E) trait, and POSOP's value as a decision support tool (VAL) accounted for 54% of the variance explained by their intention to use POSOP (I). All these variables (AT, PBC, E, and VAL), except their subjective norm (SN, b = -0.03), directly influenced their intention to use POSOP (I) (b = 0.64, -0.16, -0.14, and 0.13 respectively). In addition their intention to use POSOP (I) was also indirectly influenced by POSOP's perceived value as a decision support tool (VAL) (b = 0.25, Table 6.11) with a substantial effect via their attitude (b = 0.21, not shown in the Table and in the model).

Unlike the model of extension agents' perceived usefulness of POSOP, although its value as a decision support tool (VAL) directly influenced their beliefs about (BB), and their evaluation of expected outcomes (EO) from using POSOP (b= 0.40 and 0.41), these beliefs (BB), and their view of expected outcomes (EO) had little, or no direct effect on their attitude towards the use of POSOP (AT) (b = 0.08 and 0.11). These beliefs (BB), and their view of expected outcomes (EO), and POSOP' s value as a decision support tool (VAL) all accounted for 17 % of variance explained by their attitude towards the use of POSOP (AT). Only POSOP's value (VAL) directly influenced their attitude towards using it (AT) (b = 0.32). POSOP' s user interface (UI) had neither direct nor indirect effects on neither their attitude towards the use of POSOP (AT), nor their intention to use it (I); however, it contributed to its value as a decision support tool (VAL).

As with the previous model, their beliefs about specific significant others (farmers, organisation, and peers) expecting them to use POSOP (SO), and their motivation to comply with their referents (MS), directly influenced their subjective norm (SN) (b = 0.20 and 0.40), and accounted for 20% of the variance in their subjective norm (SN). However, their subjective norm (SN) had little, or no, effect on their intention to use POSOP (I) (b = -0.03).

**Table 6.11** Standardised indirect effects of the model of extension agents' attitude towards the use of POSOP (ATP).

| | UI | VAL | GPA | O | E | PBC | BB | MS | SO | EO | SN | AT |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **BB** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **MS** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **SO** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **EO** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **SN** | 0.04 | 0.05 | 0 | -0.04 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **AT** | 0 | 0.07 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **I** | 0 | 0.25 | 0 | 0 | 0 | 0 | 0.05 | -0.01 | -0.01 | 0.07 | 0 | 0 |

Their intelligence, as expressed in their GPA, had neither direct nor indirect effects on their intention to use POSOP (I).

The relationships between POSOP' s user interface (UI) and its value as a decision support tool (VAL), and between this value (VAL) and the openness trait (O) were discussed in section 6.4.1.

In summary, among the variables external to the TPB, POSOP' s value as a decision support tool had substantial effects – both direct and indirect – on extension agents' intention to use POSOP (I). However, its user interface (UI) had neither direct nor indirect effects on neither their attitude toward the use of POSOP (AT), nor intention to use it (I). It did, however, contribute to its value as a decision support tool (VAL). The introvert agents had a clear intention to use it relative to the extrovert ones. This is an interesting, and logical, result. Less people oriented agents relate to a computer system.

## 6.5 Conclusions and Discussion

Clearly, the agents' beliefs of POSOP's value as a decision support tool (VAL) had a substantial impact in both models (ATU and ATP), on the agents' attitudes towards its use (b=0.29 and 0.13). The same was the case for extension agents' perceived usefulness of POSOP, and extension agents' attitude towards the use of POSOP (ATs) (b = 0.23 and 0.64). Similarly, perceived behavioural control (PBCs) had a substantial impact on the intention to use POSOP (b = -0.17 and -0.16), but the subjective norm (SN) had little, or no impact (b = -0.06 and -0.03). In Model ATU, these three variables plus POSOP's value as a decision support tool (VAL) accounted for 21% of the variance in POSOP use intention, and in the ATP model the variables plus the Extraversion (E) trait accounted for 54% of the variance.

Overall, the VAL, UI, E, O, group and GPA explained 7% and 5%, VAL explained 7% and 2%, and PBC explained 3% and 2% of the variance in the POSOP use intention in Models ATU and ATP. The Extraversion (E) trait explained 3% of the variance in POSOP use intention in Model ATP. The user interface (UI) explained 4%

of the variance in the agents' perceived usefulness of POSOP (AT) in Model ATU. This is an interesting result as the interface is analogous to the communication between an expert and a client. It is an important feature in developing expert systems (Table 6.12).

**Table 6.12** Total variance explained.

| | **ATU** (%) | **ATP** (%) |
|---|---|---|
| Total intention (I) variance explained | 21 | 54 |
| Intention (I) variance explained by VAL, UI, E, O, and GPA | 7 | 5 |
| Intention (I) variance explained by VAL | 7 | 2 |
| Intention (I) variance explained by PBC to intention (I) | 3 | 2 |
| Intention (I) variance explained by E | - | 3 |
| Attitude (AT) variance explained by UI | 4 | - |

**ATU:** A model of extension agents' perceived usefulness of POSOP.
**ATP:** A model of extension agents' attitudes towards the use of POSOP.

As mentioned earlier, this study not only attempts to predict extension agents' intention to use POSOP, but also to explain the agents' personal-psychological process underlying their intention to use it. This process was then investigated.

### 6.5.1 Effect of Extension Agents' Attitudes towards POSOP's Features on Their Intention to Use POSOP.

In both models, value (VAL) had substantial effects – both direct and indirect – on extension agents' intention to use POSOP (I). In addition, the user interface (UI) was associated with the agents' perceived usefulness of POSOP, but was not associated with their attitude towards the use of POSOP. However, it did contribute to its value as a decision support tool.

These results further emphasise the importance of the user interface, as suggested by a number of authors (Broner, Parente and Thomson, 1992; Hockman, Pearson and

Litchfiled, 1994; Nuthall and Bishop-Hurley, 1996a; Wolak and Carton, 1992). Efforts to improve the user interface, based on the agents' suggestions, may well enhance its value, and thus increase the agents' positive attitudes towards, and intention to, use POSOP.

It is worth tracing factors underlying POSOP's value and its user interface. According to the agents, the accuracy of diagnosis, and the applicability of advice, together with the credibility of the expert from which POSOP's knowledge base is developed seemed to be the main factors in its value. For the interface, clarity of wording, informativeness, quality and size of photos, type, size and colour of font, and background colour all seem to be the important factors in the interface (Appendix D, Section C).

In addition, POSOP's good features (Appendix F, Table F1) will no doubt be largely responsible for the agents' attitude towards using POSOP. These include (1) ease and convenience of use, (2) provision of quick diagnosis and timely decision support, (3) ease of understanding, and (4) clarity of pictures and text.

In improving POSOP, attention should be directed to the agents' comments on POSOP's bad features (Appendix F, Table F2). These included (1) some pictures displayed were too small, (2) more variety of sample pictures is needed, (3) some information needed further explanation, (4) more diseases needed to be covered, (5) some symptom descriptions were not clear, (6) pest and storage insects, and natural predators needed to be covered.

### 6.5.2 Effect of Extension Agents' Attitudes on Their Subjective Norm with Regard to Using POSOP.

Although value (VAL) and the user interface (UI) was associated with the agents' beliefs about significant others (SO), and these beliefs was associated with their subjective norm (SN), the agents' subjective norm (SN) had little, or no impact on their intention to use POSOP (I). Armitage and Conner (2001)'s meta-analytic review revealed that a function of measurement was responsible for the poor predictability of subjective norm (SN) as most of the TPB studies used single-item measures.

Furthermore, Conner and Armitage (1998) noted that normative influence conceptualised in subjective norm, in the TPB/TRA framework, failed to tap important components of social influence. However, neither the measurement function, nor the tapping of social influence, was able to explain the poor explanatory performance of subjective norm. Furthermore, the agent's beliefs about their specific referents (SO) – farmers, DOAE, and peers, and their motivation to comply with these specific referents (MS), clearly associated with their subjective norm (SN) ($b = 0.20$ and 0.40). The poor explanatory performance could be due to the relative strength of the agents' attitudes (ATs), subjective norm (SN), and perceived behavioural control (PBC). Social pressure to use POSOP, as perceived by the agents, was not as strong as their attitudes (ATs) and perceived behavioural control (PBC). Extension agents believed that their specific referents would want them to use POSOP (2.92, 3.35, and 3.19 out of 4 respectively), and were motivated to comply with these specific referents (3.00, 3.19, and 2.80 out of 4 respectively). Their generalised motivation to comply with their referents (MS) had twice the effect of their beliefs about their referents' expectation to use it (SO) ($b= 0.40$ and 0.20). Clearly, there was a tendency towards using POSOP if their specific referents, especially their organisation, expected them to do so. However, as extension agents are professionals, their perception of generalised social pressure might not strongly influence their judgement on using POSOP as a decision support tool.

In summary, the agents' intention to use POSOP (I) was largely determined by their perceived usefulness and their attitudes towards its use (ATs), which in turn was influenced by their attitudes towards POSOP' s value (VAL) and its user interface (UI). Also their intention (I) was partly determined by the agents' perceived behavioural control (PBC). The agents' subjective norm (SN) had the weakest impact on their intention to use POSOP (I).

### 6.5.3 Effect of Extension Agents' Personality Traits on Their Attitudes towards the Use of POSOP.

Extension agents' personality traits, both Openness (O) and Extraversion (E) had no impact on their perceived usefulness of POSOP in Model ATU. In other words, 'open' and 'closed' agents were not reliably different with regard to their evaluations of the utility of POSOP. This also applied to the 'extroverted' and 'introverted,' agents. However, Extraversion (E) had a slight negative impact ($b = -0.14$) on the agents' intention to use POSOP in Model ATP. As hypothesised, the 'introverted' agents had a clear intention to use POSOP relative to the 'extroverted' agents.

Although Openness (O) had a direct effect on the agents' beliefs about their specific referents expecting them to use POSOP (SO), it had little, or no, effect on their subjective norm (SN) and intention to use it (I). The less 'open' an agent, the stronger their beliefs about their specific referents expecting them to use POSOP. As Costa and McCrae (1992b, p. 17) noted, "Closed individuals tend to accept authority and honour tradition and as a consequence are generally conservative." This might explain why the agents had strong beliefs about their organisation expecting them to use POSOP as well as a strong motivation to comply with their organisation. However, it should be noted that the Openness (O) trait in the Thai culture measured by the NEO-FFI was problematic. The shortened scales, NEO-FFI (Form S of the NEO PI-R), are somewhat less reliable than the full NEO PI-R. Thus the full NEO PI-R, in particular the specific facet, 'O5:Ideas' is recommended for any future research as this facet is seen as a willingness to consider new, perhaps unconventional ideas (Costa and McCrae, 1992b). Further research on the Openness (O) trait in Thai culture is required.

### 6.5.4 Effect of Extension Agents' Intelligence on Their Attitudes towards the Use of POSOP.

Extension agents' intelligence, in terms of their GPA, had no association with any of variables in the TPB, and the variables external to the TPB. It could be that the agents' level of intelligence was largely similar – thus no variability existed to allow relating the variance to attitude.

The facets of Openess (O) were correlated with divergent thinking. These facets were Fantasy, Aesthetics, Feelings, Actions, Ideas, and Value, and had correlation coefficients of 0.21, 0.23, 0.28, 0.17, 0.31, and 0.25 (McCrae, 1987). This suggests that the 'Ideas' facet may be used in future research on personality, intelligence, and attitude relationships. However, intelligence should be strictly defined and its testing in the Thai culture should be developed.

### 6.5.5 Effect of Extension Agents' Perceived Behavioural Control on Their Intention to Use POSOP

It is useful to investigate the control beliefs underlying extension agents' perceived behavioural control (PBC) as this might reveal specific barriers that prevent the use of POSOP. Their PBC was found to be highly and significantly correlated with their beliefs in their own knowledge and skills (KSK) in using POSOP ($r = 0.43$), It was not, however, correlated with their beliefs about the facilities available (FAV) for using POSOP ($r = -0.05$). This indicated their beliefs in their own skills were the important factor in influencing their perceived control over using POSOP (PBC). Although extension agents perceived they had poor computer skills (2.99 out of 4), they believed either operating a computer, or using POSOP, would not be difficult (as expressed by their response of 1.38 and 1.07 out of 4 for, "Using or operating a computer would be difficult," and "Using POSOP would be difficult."). Still, they strongly agreed (3.64 out of 4) that, "Having training on how to use POSOP would be beneficial."

The lack of an association between their perceived behavioural control (PBC) and the facilities (FAV) should not be interpreted as indicating that the facilities were not important. POSOP requires both software and hardware. This lack of association could be due to the variation of computer facilities between offices – both in number and capacity. The agents believed they had an adequate number of computers (2.26 $\pm$1.25 SD), but they were not sure whether the computers available were of sufficiently high capacity (1.73 $\pm$ 1.13 SD). In addition, extension agents' opinions about the adequacy of their own knowledge, accessibility to information sources, and their organisation's expectation should give rise to ideas for strategies promoting POSOP. The agents agreed that learning sufficient knowledge would not be easy, nor would obtaining information from others, and nor would this information be timely. This implies the agents would turn to POSOP as an alternative source of information, or as a tool to train themselves in rice disease diagnostic skills. They strongly agreed that funding by the Department of Agricultural Extension (DOAE) would be beneficial, they didn't believed the cost of using POSOP would be expensive, and also agreed that if they had to use POSOP at their own expense this would still be worthwhile.

Overall, extension agents' control beliefs and opinions suggested that if POSOP is to be put into effective operation in extension work, suitable computers and institutional support, as well as training on how to use POSOP, should be provided.

# CHAPTER 7
# Summary and Implications

## 7.1 Introduction

Integration of a new technology into an organisation is a complex process. Focusing on only one factor (e.g., the expert systems' attributes, or user characteristics, or the institutional support), may not provide an adequate understanding of the problem as a whole. Thus, this research focused on the holistic view of the problem by integrating all these factors in a framework through developing an operational model of extension agents' attitude towards the use of an example expert system (POSOP).

In this Chapter the findings from the literature and the model of the extension agents' attitudes are summarised. The summary of the findings is organised according to the research objectives. The study attempted to investigate:

(1) the effect of extension agents' view of an expert system's features, in particular its value as a decision support tool and its user interface on their attitudes towards its use;
(2) the effect of extension agents' personality traits, in particular the Extraversion (E) and Openness (O) traits, on their attitudes towards its use; and
(3) the effect of extension agents' intelligence, in terms of their grade point average (GPA), on their attitudes towards its use.

First, factors influencing the acceptance of agricultural expert systems are summarised. Next, implications for future research are presented. Then, the associated implications for the utilisation of expert systems in Thai agricultural extension services are summarised and discussed.

## 7.2 A Summary of the Factors Influencing the Acceptance of Agricultural Expert Systems

Since the actual use of an example expert system could not be measured in this study, the relationships between perceived control over using the system and intention to use it, and the actual use could not be explored. Thus, the study focuses on the contributions of attitude, subjective norm, and perceived behavioural control, plus the variables external to the TPB, to the prediction and explanation of intention. It is assumed, therefore, that the actual use is correlated with intention. Measuring the actual use will have to wait until several years have passed.

It is clear that acceptance of an agricultural expert system by its potential users is associated with a number of factors, including the attributes of the system, user characteristics, and the support of the system. Understanding these factors would be useful for strategic planning in gaining a greater uptake of this technology by extension agents and farmers, and support of the systems by the institutions.

### 7.2.1 Expert Systems Attributes

A review of literature revealed that, to be successful, a system must deal with significant problems that respond to the potential users' needs. Not only must it be accurate and reliable, but it must also be useful, as perceived by its users. Its solutions must be timely and quickly available, and it must be easy to use. Even the most powerful expert system will not be applied if it requires too much effort on the part of the user. The user interface is regarded as a critical factor in its acceptance by extension agents and farmers. Whether or not an expert system achieves success may be determined by the nature of its user interface.

The study made it clear that the agents' attitude towards an expert system's value had a substantial impact on both their perceived usefulness of the system and their attitude towards using it, and their intention to use it. The agents' attitude toward an expert system's user interface also had an impact on their perceived usefulness, but had no impact on their attitude towards using it. However, it did contribute to its value as a decision support tool. Above all, the study emphasised the importance of addressing both the agents' 'significant' problems and their 'urgent' needs. Systems meeting these needs are likely to be well accepted. As Davidson and Voss (2002) note

> "…many IT designers follow the *Field of Dreams* approach – that 'if you build it, they will come.' In contrast, there is a considerable body of research that deals with how technology is defined, used, and evaluated by those that are tasked with adopting it. Not surprisingly, the evidence is clear the *Filed of Dreams* approach rarely succeeds as expected."
>
> Davidson and Voss (2002, p. 76)

Davidson and Voss (2002) discuss the two models on which information systems are based. These are technological deterministic and social constructivist models. In the technological deterministic or conventional model, the parameters of the system are defined, and the problems of adoption and integration of the system into pre-existing patterns of work is not assumed. Once the new system is put into operation, it forces a wide change in workplace behaviour and attitude towards the value of the system. To figure out this approach is that once the system is complete, it is simply "thrown over the wall" to users. The users are trained to use the system. The system is then integrated into the users' working lives. Users have to adapt to it. This model sees technology as the key driver of organisational form and change.

In contrast, the social constructivist model, the emerging best practice, places much more emphasis on user involvement in defining, designing, and disseminating the new information system. The model focuses on the 'social life' of the technology required by end users, and there is clear emphasis on how the new system will be integrated with the users' working lives. In this view, users are seen much more as co-system developers rather than mere customers. In this model, the organisational culture plays a significant role in shaping technology that will be actually used.

In retrospect, the technological deterministic or conventional view can be seen as the 'top down' approach because the developer imposes systems on users, whereas the social life approach can be seen as the 'bottom up' approach because the system is co-defined and co-designed by the users based on their needs. In the conventional view, the identification of barriers among users resistant to the new system is required, whereas the constructivist view, the identification of the user needs has paved the way for its dissemination. Finally, the conventional approach tends to lead to systems being used by users for differently intended purposes, whereas the 'social life' view ensures the developers and users are clear about the requirement and practicality of the system. The significance of the constructivist view is that it highlights the role of workplace culture as a key to the long-term success, that is adoption, integration, and use of any new information system.

Involvement of users in system development can be achieved by identifying user needs and attitudes, modifying the system after observing users' reactions to the system at various stages of the development cycle, evaluating both the usability of the system in the workplace and acceptability of recommendations given by the system, and getting users directly involved in the development of the knowledge base (Hochman, Pearson and Litchfiled, 1994).

Not surprisingly, as the example expert system (POSOP) used in this study was developed from the social constructivist view, and the agents were asked to identify their own problems and needs in the preliminary survey on the need for expert systems as decision support tools in Thailand (Appendix D), the agents made it clear they had a strong intention to use it. It is important to know where their strong intention to use POSOP came from and how their intention (behavioural plan) and behaviour (actual use) can be reinforced. Thus, the agents' intention to use POSOP was traced. Not only was their intention directly influenced by POSOP's value, but also by the agents' perception of its usefulness and their attitude towards using it, in turn, were directly and indirectly influenced by its value and its user interface. This emphasises improvements to its 'value' and 'user interface,' as suggested by the agents, are likely to enhance its potential use. This might be achieved by expanding the knowledge base and diagnostic content to cover additional diseases, pest and storage insects, as well as natural predators (see Appendix F, Table F2).

While all these interface factors may seem trivial, it is these small matters that may be the key to acceptance. They can be fixed quickly whereas improvements to POSOP's value will require more time and effort; particularly if the knowledge base is expanded. This calls for the cooperation of expert (s) from a wide range of fields.

Ease and convenience of use seem to favour POSOP's use, as does its quick diagnosis and timely decision support, its ease of understanding, and its accuracy and diagnostic credibility.

### 7.2.2 User Characteristics

Perhaps the most important factor in expert system technology acceptance is the users themselves. Unfortunately, a review of literature indicated only a limited amount of research on demographic and socio-economic characteristics of expert systems users has been conducted (Adoum, 1992; Nuthall and Bishop-Hurley, 1996b). The findings of this current work have provided a fundamental understanding of the characteristics of the potential users. It has become increasingly clear that perceived usefulness and ease of use are the two factors long recognised as key to user acceptance of information systems, the former being the more important (Davis, 1993; Keil, Beranek and Konsynski, 1995). This finding provided a rationale for redirecting efforts to explain technology adoption. The shift was from computer uptake and computing expertise to what an expert system, as a decision support tool, offers the user, and its usefulness in improving decision-making and alleviating problems. Users' perception of the system's value as an alternative decision support tool must be a crucial factor influencing the acceptance of the system. Unfortunately, less effort has been made in the past to investigate this factor.

While research studies would suggest the extension agents' perceptions of the usefulness of the system (Davis, 1993; Kiel, Beranek and Konsynski, 1995), and its user interface (Broner, Parente and Thomson, 1992; Hockman, Pearson and Litchfield, 1994; Nuthall and Bishop-Hurley, 1996a; Wolak and Carton, 1992), are important influences on user attitudes towards its use, the factors influencing the perception of usefulness, which are thought to be psychological characteristics such as personality and intelligence, have not been studied in the past. This study has moved in this direction.

Two personality traits – Openness (O) and Extraversion (E) were evaluated. As hypothesised in Model ATP, Extraversion (E) had a negative impact on the agents' intention to use an expert system (POSOP). 'Introverted' agents had a clear intention to use the decision support tool relative to 'extroverted' agents. This would be expected with introverts' lack of keenness to interact with people. However, in Model ATU neither

Openness (O) nor Extraversion (E) impacted on their perceived usefulness of an expert system. Thus, 'open' and 'closed' agents were not reliably different with regard to their evaluations of the utility of POSOP. Similarly, 'extroverted' and 'introverted' agents were not reliably different. In other words, in Model ATU an expert system was considered useful regardless of the agents' personality background.

Extension agents' intelligence, in terms of their GPA, did not have an impact on their attitude, nor their subjective norm, regarding the use of POSOP, and had no association with any of the variables in both models. This may have been due to the agents all having a similar level of education.

### 7.2.3 Institutional Support of a System

Besides the systems' attributes and user characteristics, the success of an expert system may depend on the agents' perception of control over using the system. This might be the place where institutions can play a significant role in changing the perceived control over using the system, and in support of system development.

A review of literature revealed user attitudes towards a computer alone does not determine the actual use of a computer. The amount of training and ease of access to a computer are the most important factors in human service organisations. If they wish to introduce computers, or computerised information systems, they must provide sufficient training, involve professionals in the development of the information systems, provide easy access to technology, and attend to the structural factors of the organisation that could facilitate, or impede, the adoption of a new technology (Mutschler and Hoefer, 1990). These views are likely to be applicable to the introduction of expert systems in Thailand.

Generalised perception of control over using POSOP and its determinants (perceived own knowledge and skills, and the facilities available) were studied. The results showed the agents' generalised perceived control over using POSOP had a substantial effect on their intention to use POSOP in addition to their attitude. In general, the agents perceived they would not have difficulty in using POSOP. Although they perceived they had poor computer skills, they believed either operating a computer or using POSOP would not be difficult. Still, they did believe training would be beneficial. It seems the agents were more concerned about the facilities available for using POSOP as some agents put it, 'if resources were not available to support POSOP use, there was no benefit in promoting its use.' Furthermore, they suggested the system development should be supported by a higher level office (perhaps, the Provincial Office, the Regional Office, or the Department of Agricultural Extension). This is an expected institutional response. They would be worried that their office would bear the cost leading to a reduction in their current activities – a simple trade-off.

Availability of suitable computers seems likely to impede the use of POSOP. While the agents believed they had enough computers in their offices, some agents complained that they had difficulty in accessing a computer since it was often reserved for administrative tasks. Even though the agents have a strong intention to use POSOP, these barriers must be removed if this example system is to put into effective operation. This implies providing suitable computers and easy access to a computer, coupled with training. Administrators need to be aware that, in general, only 10% of automation expenses are for hardware, whereas 40% are for software and 50% are for training (Mutschler and Hoefer, 1990).

## 7.3 Implications for Future Research

Although this research is constrained by a small sample size, it provides a holistic view on the factors determining the primary acceptance of expert system technology in an extension service organisation. The models explain the personal-psychological processes underlying the extension agents' intention to use an expert system and predict it is likely that the system will be well accepted. This might be because it was developed for the agents' main problem that urgently required a solution, as well as its perceived value and user interface. However, POSOP is not fully mature, and still needs revising. Future research should be directed towards two directions – practical and theoretical.

In the practical direction, improvements to POSOP's value and its user interface, as suggested by the agents, should be made. This will reinforce their favourable attitude and intention to use it. The revised version should be re-tested in a larger sample and its use followed through in the workplace over several years to determine whether the explanatory models developed explain attitudes and use, and whether they can be generalised. A factor that emerged from the agents' complaints that should be taken into account is their poor 'access to a computer.' This factor should be included in the model as a control belief in addition to their own knowledge and skills in, and the facilities available for, using the system. This might reflect a social barrier hidden in the workplace, or it might imply there are not enough computer facilities in some District Agricultural Offices. The institution can play a significant role in removing these barriers. Remedies include either providing more computer facilities if there is no restriction on the budget, and/or managing efficient use of the limited resources (e.g. providing booking timetables and making sure that each agent and administrative staff have a fair opportunity to access a computer).

In theoretical sense, both models suggested Openness (O) had an influence on the agents' beliefs with regard to specific significant others (farmers, organisation, and peers) expecting them to use POSOP. However, interpreting these relationships should be made with precaution. It should be noted that the Openness (O) trait in the Thai culture measured by the NEO-FFI was problematic. This might be due to, on one hand, the culture difference. On the other hand, the shorter scales, NEO-FFI (Form S of the NEO PI-R), are somewhat less reliable than the full NEO PI-R.

Both models suggested that GPA had no association with any of the variables in the models. Model ATU suggested that POSOP was considered useful regardless of the agents' personality background. Thus, GPA, Openness (O), and extraversion (E) may be dropped from the model in future research. In Model ATP, extraversion (E) accounted for 3% of POSOP's 'use intention' variance, while POSOP' s value (VAL) and perceived control over using POSOP (PBC), each accounted for 2% of the 'use intention' variance. Thus, GPA and Openness (O) may be dropped from the model in future research. Dropping these variables reduces the number of the variables and their associated parameters, thus improving the model's parsimonious nature, and increases the efficacy of the model.

An interesting result emerged from both models. The simplified models are given in Figure 7.1 and 7.2. Assuming all things being equal, the two models revealed the different psychological processes of extension agents' intention to use POSOP. Their perceived usefulness seemed to be based on objective thinking and reasoning processes, or cognitive evaluation, while their attitude towards the use of POSOP seemed to depend on their

**Figure 7.1** The simplified model of extension agents' perceived usefulness of POSOP (ATU).

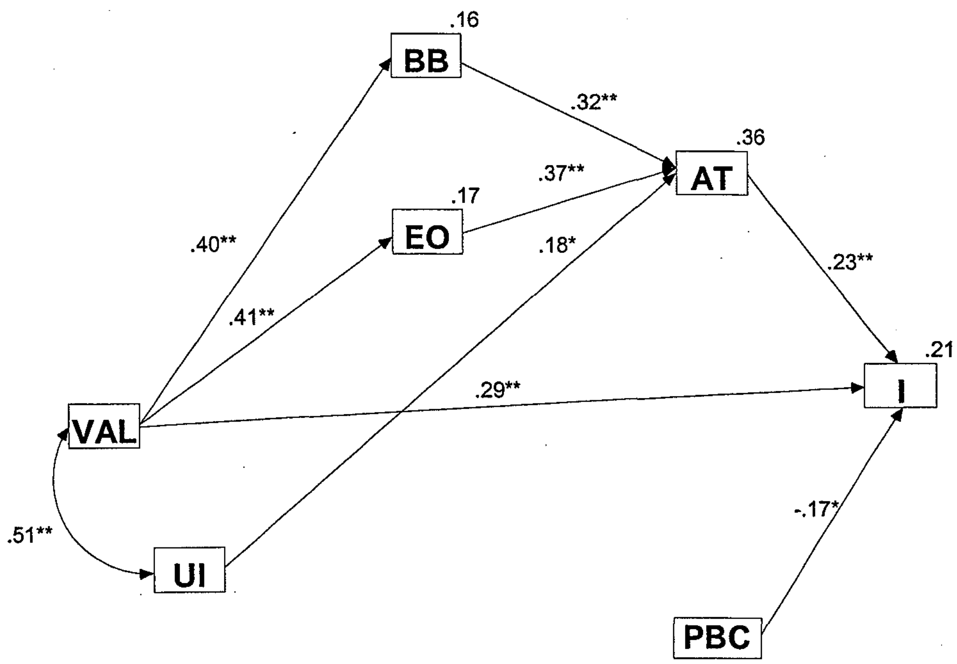
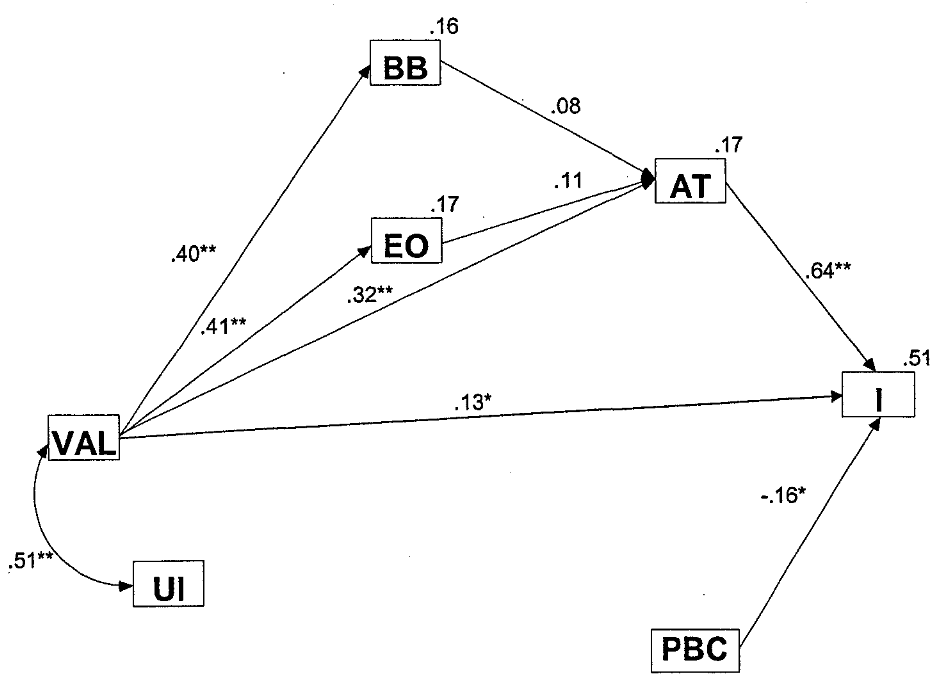



**Figure 7.2** The simplified model of extension agents' attitude towards the use of POSOP (ATP).



subjective feelings, or affective evaluation. However, both cognitive and affective evaluations might have joint effects on their attitude towards the use of POSOP, and thus their intention to use it. Haddock and Zanna (2000) summarised the results of several studies that provide support for the joint effect of beliefs (cognition) and feelings (affect) on evaluations.

In both models, POSOP's perceived value as a decision support tool (VAL) had substantial direct effects on extension agents' intention to use it (I). This result was consistent with the classic view of attitude towards a psychological object (Thurstone, 1931; cited in Ajzen and Fishbein, 2000). Extension agents' favourable, or unfavourable, attitudes towards POSOP's features – its value as a decision support tool (VAL) and its user interface (UI) – may be automatically activated from exposure to the system without conscious intent or cognitive effort, and this attitude then created their planned behaviour relating to the object (intention to use it). They may well be consciously unaware of this process.

However, Model ATP accounted for more than twice the 'use intention' variance compared to Model ATU. The attitude towards the use of POSOP had three times the effect of the agent's perceived usefulness of POSOP. The path of this impact was traced. In Model ATP, POSOP's value (VAL) influenced their intention to use it (I) merely via their attitude towards its use (AT). In contrast, in Model ATU, the path was through their beliefs about (BB), and evaluation of expected outcomes (EO), and their perceived usefulness of POSOP (AT).

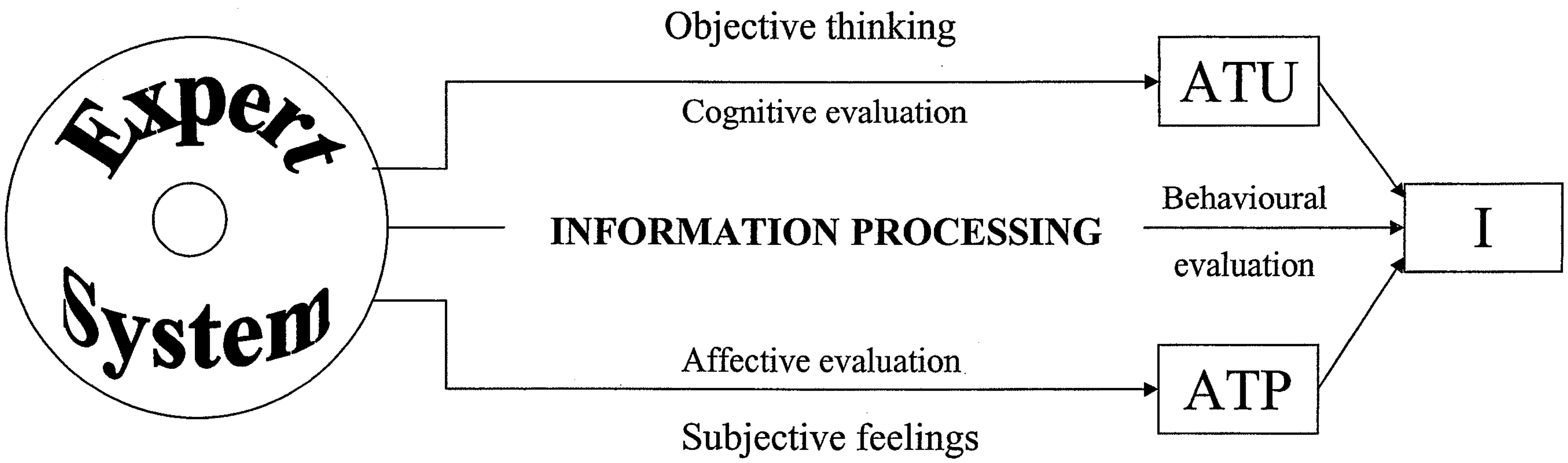
In this study, it is possible that when the extension agents were exposed to POSOP (attitude object), and tried using it (obtaining more information about its features and how it works), their beliefs and views of expected outcomes were deliberately formed (cognitive evaluation process), and thus their perceived usefulness of POSOP was created. On the other hand, the agents' attitude towards its use might well be subconsciously formed in parallel regardless of their beliefs about (BB), and views of expected outcomes from (EO) using it (affective evaluation process).

All these three processes are summarised in a tripartite model of cognitive-affective-behaviour influence on extension agents' attitude towards the use of an expert system (Figure 7.3). The tripartite model can be thought of as an integration of the two models and the classic view of attitude towards a psychological object, where the upper, and lower paths of the model represent the models of extension agents' perceived usefulness of POSOP (ATU), and their attitude towards its use (ATP). The middle path of the model represents the classic view of attitude towards an object.

The tripartite model suggests that the affective and cognitive components of extension agents' attitudes towards the use of an expert system might be controlled by different-interdependent systems. This is supported by Zajonc (1980, p. 151) concluding, "affect and cognition are under the control of separate and partially independent systems that can influence each other in a variety of ways, and that both constitute independent sources of effects in information processing," and similarly, Fazio (1990, p. 97) also noted that "an overall attitude towards the behaviour process that is essentially deliberative in nature might still involve some components that are automatised. Likewise, the essentially spontaneous process itself may sometimes involve some components that are controlled."

It could be that extension agents' beliefs about POSOP (BB), and their view of expected outcomes (EO), might fail to tap the extension agents' affective beliefs and view of outcomes. Thus, the association between both their perceived usefulness of POSOP (AT) and beliefs about (BB), and their view of expected outcomes (EO) from using POSOP was not found in Model ATP. It would be useful if affective beliefs were tapped and included in the model. This will not only disclose the beliefs underlying the agents' attitude towards the use of an expert system, but also provide a better understanding of the structures and processes underlying the cognitive and affective components of the agents' attitudes towards its use. Affective evaluations have gained attention from social psychologists. It remains debatable whether it is better to tap such affective beliefs as beliefs underlying attitude (in parallel to other behavioural beliefs) or as a predictor of intentions (Conner and Armitages, 1998). However, further research specifically designed to test the tripartite model needs to be conducted. An area that might be useful is assessing the contributions and associations of the three processes in explaining attitude and intention. This might lead to a different theory. In the meantime, the research has led to a better understanding of how people, in this case extension agents, view innovations. This understanding should lead to the development of improved systems and their effective utilisation in the world of computer based decision support systems.

**Figure 7.3** A tripartite model of the cognitive-affective-behaviour components of extension agents'attitude towards the use of an expert system.




ATU: Perceived usefulness of an expert system.

ATP: Attitude towards the use of an expert system.

I: Intention to use an expert system.

## 7.4 Implications for the Utilisation of Expert System Technology in Thai Agricultural Extension Services.

Since expert systems were developed before any understanding about how to organise it within a larger social context, society has not yet absorbed the full significance of expert systems, particularly in the Thailand context. Their primary role as a decision support tool has long been known; however, their other potential roles, such as an extension or technology transfer tool (Gum and Blank, 1990; Plant and Stone, 1991, Rafea, 1998), a training tool (Fidanza and Waddington, 1990; Nash et al., 1992; Rafea and Shaalan, 1996; Stewart, 1992; http://www.sbaer.uca.edu/Research/1999/WDSI/ 99wds650.htm, 2004), an educational tool (Fidanza and Waddington, 1990; Broner, Parente and Thompson, 1992; Pasqual, 1994), and a human expert assistant (Hart, 1986; Ganeshan and Chacko, 1990) have been stressed.

The findings of the POSOP research reinforce the idea of an expert system acting as a training tool for extension agents. Its role in this way, as expressed by the agents, has become obvious (98.3% of the agents would use POSOP to train themselves, and 89.7% would use POSOP as a decision support tool). Furthermore, almost all of the agents (98.4%) believed a wide-range of well-prepared expert systems had a potential to help them. The potential application for expert systems in agricultural extension, as suggested by the agents (Table 7.1), is broad. The major problem areas include production management, pest insect management, soil-water-fertiliser management, disease management, agribusiness and farm management. Sophisticated programs that capture the judgmental knowledge of a human expert can serve almost all sectors of the agricultural community.

Although expert systems hold promise for various applications in agricultural extension, expectations raised for their development should be tempered by the realities of their cost and also their long-term usefulness. As the knowledge-base in many of these areas is relatively small, experience would suggest that agents would use the tool to develop their own innate or tacit knowledge and therefore not need the expert system in the future. A problem addressed by an expert system should be truly meaningful, and solutions offered by the system must be significantly useful to justify the cost. Solutions must be accurate, reliable, and applicable so the user will have confidence in decisions made by the system and the solutions applicability.

Introducing expert systems to the Thai agricultural extension services is likely to:

(1) help improve extension agents' performance, particularly the quality of their decision-making skills in solving problems beyond their knowledge and expertise,
(2) save the agents' time searching for information and provide faster and timely solutions to farmers, and thus enhance extension service efficiency,
(3) provide a training tool for novice agents, and as a reminder for the experienced agents,
(4) compensate for scarce human experts, particularly where the scarcity of experts in the field is a problem, and the problem exists over many areas. (In the Thai setting, the problem of retaining human experts could be worse due to the impact of the early retirement policy imposed by the 8th (1997-2001) and the 9th (2002-2006) National Social and Economic Development Plan (http://www.infonews.co.th/CSC/detail.htm; http://www.infonews.co.th/CSC/june7.htm, 1999; http://businessworld.ocsc.go.th/web/MainLink1.asp, 2004), and
(5) preserve the Department of Agricultural Extension' s knowledge and expertise which is vital for its future. The knowledge accumulated during years of experience by extension experts is often poorly documented and tends to be lost when an individual retires.

Introducing this technology calls for collaborative efforts and support from the relevant parties – experts, knowledge engineers, and users, both at the personnel and the institutional level to ensure the effective development, operation, and maintenance of systems. However, it is clear that not only successful knowledge acquisition is crucial, but also a good supply of knowledge engineers, particularly in agricultural organisations. Clearly, a shortage here creates a bottleneck in developing agricultural expert systems (Plant and Stone, 1991).

**Table 7.1** Potential problem areas that extension agents believe expert systems could be valuable.

| Potential problem areas | Number * |
|---|---|
| Production management in fruits trees, vegetables, ornamental plants, livestock, and fresh water fish | 69 |
| Pest insect management in rice, fruit trees, vegetables, and ornamental plants | 48 |
| Soil-water-fertiliser management | 30 |
| Disease management in fruit trees, vegetables, ornamental plants, livestock, and fresh water fish | 26 |
| Agribusiness and farm management, marketing analysis, accounting | 13 |
| Post-harvest management, produce quality control, and food processing | 8 |
| Group administration and management | 5 |
| Safe chemical use | 4 |
| Weed control | 3 |
| Crop variety | 2 |
| Plant propagation | 2 |
| Drought and flood forecast | 1 |

* Number of agents mentioning the problems. Maximum number of responses = 130.

If expert systems are to be integrated within organisations, some of the most successful computer adoption techniques used in an agricultural extension service, as suggested by Mincemoyer (1990, pp. 42-44), may be applicable to expert system adoption. These are:

(1) **User-oriented objective** – An overall goal for an expert system adoption project should be set up. This might be to have 80% of extension agents using an expert system. This will require appropriate decision support, self-training, and general education systems to be set up by the end of, say, a one-year project. To achieve this goal, user education and support become the highest priority activities.

(2) **Segmented population** – The total population of extension agents should be segmented according to the adopter categories (Innovators, Early Adopters, Early Majority, Late Majority, and Laggards), and then special sub-projects set up with members of the early adopter category included in these groups. This creates an

interest for the many early adopters and encourages them to actively use their influence to encourage the agents, especially members of the early majority, to participate in using the system. However, to achieve the goal, most members of the late majority also need to be involved so effort is required to gather numerous success stories to create the interest of the early and late majority users. The focus then turns to making them successful during periods of evaluation and trial.

(3) **Global education** – educational opportunities and user support should be provided to all extension agents. In order to achieve maximum adoption, user services must be available to individuals in all adopter categories and to satisfy all stages of adoption (Awareness, Interest, Evaluation, Trial, and Adoption). Training for key members of District Agricultural offices may be an appropriate starting point to begin the adoption process; however, after this initial group has received the training, it should be made available for all members of the population. Relying on a trickle-down approach of sharing information within an office will likely lead to user frustration and stagnant adoption.

(4) **Adoption specialists providing leadership** – Technological specialists tend to approach technology adoption as a series of technical hurdles; develop a superior solution and expect users to implement it. Lessons learned in technology adoption indicate it is far more of a social than a technical process. Having adoption specialists assigned to provide leadership in expert system adoption helps to keep the focus of the process on users and their needs. At a minimum, adoption oriented individuals should be assigned the responsibility for carrying out training and support activities.

(5) **Early adopter volunteer facilitators** – several extension agents from the early adopter category can be temporarily re-assigned as facilitators for adoption among their peers. These individuals should receive specialised instruction to provide support and training to agents throughout District Agricultural Offices. This strategy can work well because it capitalises on the established leadership of the early adopter. The adoption message delivered by these individuals results in more change than could have been created by technical specialists relaying the same message. These facilitators remain peers to their target population by serving as a

volunteer with most of the agents acting as facilitators are only interested because, at some point, they know they will return to their former responsibilities.

(6) **No demarcation points for users** – User frustration is one of the primary causes of failures in adoption projects. This frustration is frequently caused by users not being able to identify appropriate resources to answer questions. Many times users are required to first determine what type of problem they are having in order to contact the appropriate service entity for help. These user service demarcation points should be replaced by a single point of support information. An added benefit of this one-stop support concepts is the continual knowledge upgrade of the support specialist as he/she pursues solutions.

(7) **Synergism between technical and adoption specialists** – While leadership for an adoption project should come from an adoption specialist, technical specialists play a vital role in developing and maintaining systems and networks. In many environments, these two types of groups often seem to be in conflict over an appropriate course of action for a complex project. However, an environment of mutual respect and cooperation is needed between the specialities offered by both groups to achieve success. This synergistic relationship can be developed between technical and adoption specialists when global project goals are established that transcend the two areas. Establishing these goals and making both technical and adoption specialists understand their role in the achievement of the goals is a key responsibility of project leadership.

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# APPENDIX A*

## The Organisation Chart of the Ministry of Agriculture and Cooperatives

**The Ministry of Agriculture and Cooperatives**

**Government Agencies**

- Office of the Secretary to the Minister
- Office of the Permanent Secretary
- The Royal Irrigation Department
- Department of Cooperatives Auditing
- Department of Fisheries
- Department of Livestock Development
- Royal Forestry Department
- Land Development Department
- Department of Agriculture
- Department of Agricultural Extension
- The Cooperatives Promotion Department
- Agricultural Land Reform Office
- Office of Agricultural Economics
- National Bureau of Agricultural Commodity and Standards
- National Institute of Coastal Aquaculture

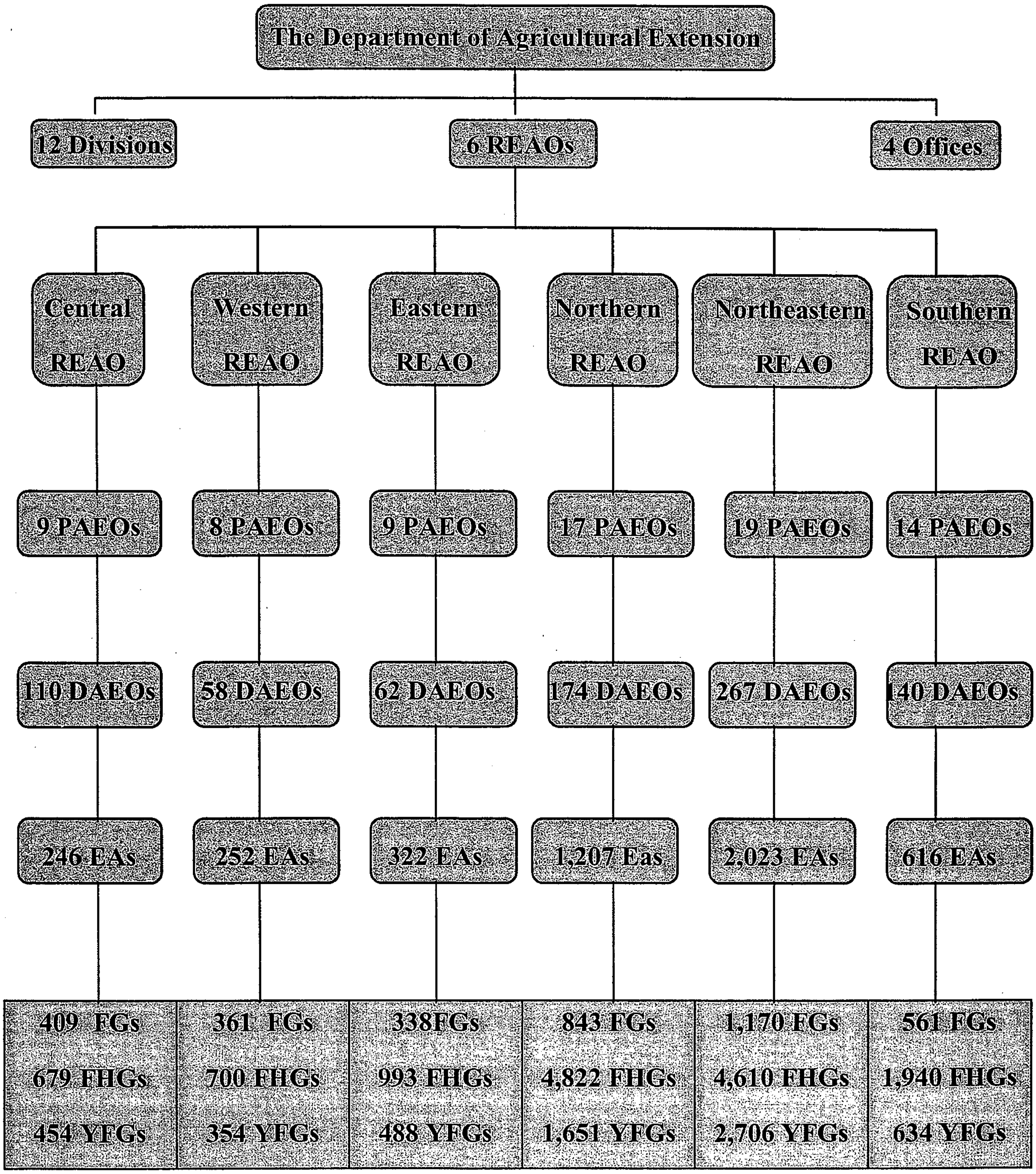
**State Enterprises**

- The Forest Industry Organisation
- Rubber Estate Organisation
- Fish Marketing Organisation
- The Government Cold Storage Organisation
- Office of the Rubber Replanting Aid Fund
- The Thai Plywood Co., Ltd.
- The Marketing Organisation for Farmers
- Dairy Farming Promotion Organisation of Thailand

**Source:** http://www.doae.go.th/menu/in_moac/in_moac.html (2003).

* See section 1.1.1 for details.

## APPENDIX B*
## The Organisation Chart of the Department of Agricultural Extension




**EAs:** Sub-district Agricultural Extension Officers; **FGs:** Farmer Groups;

**FHGs:** Farmers'Housewives Groups; **YFGs:** Youth Farmer Groups

**Source:** adapted from http://www.doae.go.th (2000)

* See section 1.1.3 for details.

# APPENDIX C*

## Preliminary Survey and Interview Questionnaire

**Survey on the Need for Expert Systems as Decision Support Tools in Thailand**

Please answer all questions, when completed, please return the completed questionnaire in the return envelope provided (no stamp required).

**Thank you for your kind cooperation in completing and returning this questionnaire.**
**Your answers and comments will be kept strictly confident.**
**Only combined response will be published.**

**Section 1 Opinions about Expert Systems**

1. Have you seen/heard about expert systems in agriculture? (Y/N) ☐
   If yes, how many expert systems have you seen/used? ☐
2. To what extent do you think that systems of capable of expert advice have a place in agricultural decision making? (please circle one of the numbers)
   (very little) 1  2  3  4  5  (very much)
3. Who do you think would use expert systems in agriculture? (please tick in one or more box)
   ☐ Teachers  ☐ Extension agents  ☐ Farmers
   ☐ Consultants  ☐ Other (please specify)__________
4. Generally, what type of farmer do you think would use expert systems?
   ☐ Beef Cattle  ☐ Dairy  ☐ Pig
   ☐ Chicken  ☐ Tiger prawn  ☐ Orchid
   ☐ Flower  ☐ Vegetable  ☐ Field crop
   ☐ Other (please specify)__________
5. If there are some expert systems that could help you make decision and provide you free of charge.
   Would you use them? (Y/N) ☐
   If not, why? (Please specify)__________
   If you have to buy them, would you use them? (Y/N) ☐
   (please specify the reason)__________

* See section 1.2.2 for details.

6. Please rank the reasons you would use the systems (1= most important, 7= least important)

6.1 Correctness and reliability of advice [ ]

6.2 Ease of use [ ]

6.3 Price of the systems [ ]

6.4 Credibility of domain expert(s) [ ]

6.5 Credibility of the developer [ ]

6.6 User interface [ ]

6.7 Other (please specify)________________________________________ [ ]

7. Do you think the reasonable price of an expert system package should be (baht) [ ]

8. To what extent expert systems could help you as decision support tools?

(Please circle one of the numbers)

(very little) 1 2 3 4 5 (very much)

9. Please rank the following problem areas you think expert systems could help make decision (by rating 1 to 5: 1 = most urgent need, 5 = least urgent need)

9.1 Diseases diagnosis and treatment [ ]

9.2 Insect diagnosis and treatment [ ]

9.3 Farm accounting [ ]

9.4 Irrigation management [ ]

9.5 Fertilisation management [ ]

9.6 Post-harvest management [ ]

9.7 Integrated crop management [ ]

9.8 Variety selection [ ]

9.9 Weed control and herbicide application [ ]

9.10 Salinity management [ ]

9.11 Financial analysis [ ]

9.12 Marketing analysis [ ]

9.13 Other (please specify)________________________________________

10. Do you have any other opinion about expert systems?

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11. What farmers' problem you find it most difficult to provide advice? Why?

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**Section 2 Computers**

1. Which best describes your computer access (please tick one box- if do not access go to section 3)

    1.1 Do not own but do have access to a computer ☐

    Where can you access? (please specify)________________________

    1.2 Currently own a computer ☐

    For how many years have you owned a computer? ☐

2. Do you share a computer? (Y/N) ☐

    With how many people? ☐

3. Does computer ever break down? (Y/N) ☐

    How long to get computer repaired? (days) ☐

4. Size of hard disk drive (Mbytes) ☐

5. Operating System/Environment (please tick one or more box)

    MS-DOS version________________________ ☐

    Windows version________________________ ☐

    Macintosh Operating System version________________________ ☐

    Other (please specify)________________________

6. On average, how many hours per week you use the computer for

    Business ☐

    Entertainment ☐

    ☐

    Other (please specify)________________________

7. How often you use the computer for business? (please tick one box)

    Daily ☐

    A regular period each week ☐

    A regular period each month ☐

    Other (please specify)________________________ ☐

8. For each of the software package listed below, rank your competence in a scale of 1 (poor) to 5 (excellent) – if do not use one leave blank.

Word processor ☐

Spreadsheet ☐

Database package ☐

Specialist package (please specify)________________ ☐

________________ ☐

________________ ☐

Other (please specify)________________ ☐

9. Can you access to any network? (Y/N) – if not go to section 3 ☐

9.1 Internet (Y/N) ☐

If yes, what do you use internet for?________________

On average, how many hours per week do you spend on internet for

Business ☐

Entertainment ☐

Other (please specify)________________ ☐

9.2 Rural net

If yes, what do you use Rural net for?________________

On average, how many hours per week do you spend on Rural net for ☐

Business ☐

Entertainment ☐

Other (please specify)________________ ☐

**Section 3 General Information**

1. What is your age in years? ☐

2. What is your sex? (F/M) ☐

3. At what level did you complete your formal education? (Please tick in one appropriate box)

Vocational College ☐

Bachelor ☐

Master ☐

PhD ☐

4. How many years have you been working as an extension agent?

(Please tick in one appropriate box)

- 1 - 5 years
- 6 - 10 years
- 11 - 15 years
- 16 - 20 years
- more than 20 years

5. How many farmers are under your responsibilities?

How many farmers can you visit?

Do you visit (please tick in one or more box)

- Individual farmer
- Group
- Both

6. On average, for how many hours per week you visit farmers/groups?

7. For how many hours per visit you spend with each farmer/group?

7. Generally, what sources and types of information do you use in your decision-making to draw conclusion before giving advice on solutions to farmers' problems?
(Please put number of hours use per week in the blank provided and rate usefulness in a scale of 1 (least useful) to 5 (most useful) in the box - if do not use one leave blank, and specify types of information).

| Sources of Information | | Types of Information |
|---|---|---|
| 7.1 Textbook ____hrs/wk | ☐ | |
| 7.2 Journal ____hrs/wk | ☐ | |
| 7.3 Farm magazine ____hrs/wk | ☐ | |
| 7.4 Newspaper ____hrs/wk | ☐ | |
| 7.5 Radio ____hrs/wk | ☐ | |
| 7.6 TV ____hrs/wk | ☐ | |
| 7.7 Internet ____hrs/wk | ☐ | |
| 7.8 Rural net ____hrs/wk | ☐ | |
| 7.9 CDROM ____hrs/wk | ☐ | |
| 7.10 Expert ____hrs/wk | ☐ | |
| 7.11 Other extension people ___hrs/wk | ☐ | |
| 7.12 Farmer ____hrs/wk | ☐ | |
| 7.13 Training course ____hrs/wk | ☐ | |
| 7.14 Other (please specify) ____ ____________________________ hrs/wk | ☐ | |

# APPENDIX D
## Preliminary Survey and Interview Results

**Table D1** Problem areas that extension agents need expert systems as decision support tools ranked by the average 'urgent need' score [a*].

| Problem areas | Average Urgent Need Score (1-5) (Mail Survey) | Average Urgent Need Score (1-5) (Interviews) |
|---|---|---|
| 1. Disease diagnosis and treatment | 1.64 | 1.06 |
| 2. Insect diagnosis and treatment | 1.75 | 1.13 |
| 3. Marketing analysis | 1.89 | 1.88 |
| 4. Variety selection | 2.27 | 2.56 |
| 5. Irrigation management | 2.28 | 3.44 |
| 6. Integrated crop management | 2.49 | 2.56 |
| 7. Fertilisation management | 2.51 | 2.81 |
| 8. Weed control and herbicide application | 2.54 | 2.31 |
| 9. Farm accounting | 2.87 | 3.06 |
| 10. Financial analysis | 2.88 | 3.38 |
| 11. Post-harvest management | 3.01 | 3.00 |
| 12. Salinity management | 3.18 | 4.13 |
| 13. Others | 3.17 | - |

[a] Average urgent need score ranges from 1 to 5, where 1 = most urgent need and 5 = least urgent need.

N = 174, except for Item 13 N = 8 in the mail survey.

N = 16 in the interview survey.

[*] See section 1.2.2 for details.

**Table D1.1** Sources of information used by the agents and their average usefulness scores [a] (From mail survey)[*].

| **Sources** | **Average Usefulness Score (1-5)** |
|---|---|
| Textbooks (n=159) | 3.94 |
| Other extension agents (n=143) | 3.73 |
| Experts (n=39) | 3.62 |
| TV (n=152) | 3.58 |
| Training (n=101) | 3.53 |
| Experienced farmers (n=145) | 3.52 |
| Journals (n=158) | 3.44 |
| Newspapers (n=144 ) | 3.28 |
| Farm magazines (n=120) | 2.99 |
| Radio (n= 110) | 2.83 |

[a] Average usefulness score ranges from 1 to 5, where 1 = less useful and 5 = most useful.

[*] See section 1.2.2 for the details.

**Table D1.2** Sources of information used by the agents and their average usefulness scores [a] (From the interviews)[*].

| Sources | Average Usefulness Score (1-5) |
|---|---|
| Own experience (n=6) | 4.67 |
| Experts (n=13) | 4.23 |
| Training (n=15) | 3.93 |
| Textbooks (n=15) | 3.93 |
| Experienced farmers (n=16) | 3.88 |
| Other extension agents (n=15) | 3.53 |
| Farm magazines (n=6) | 3.50 |
| TV (n=16) | 3.44 |
| Journals (n=15) | 3.07 |
| Newspapers (n=15) | 3.07 |
| Radio (n=2) | 2.00 |

[a] Average usefulness score ranges from 1 to 5, where 1 = less useful and 5 = most useful.

[*] See section 1.2.2 for the details.

**Table D2** Capacity of the office computer' s hard disk*.

| Capacity of hard disk (MB) | Mail survey* No. | Interviews* No. |
|---|---|---|
| 6488 | 2 | |
| 1875 | 1 | |
| 1503 | 1 | |
| 1207 | 7 | 8 |
| 850 | 3 | |
| 540 | 2 | |
| 400 | 1 | |
| 300 | 1 | |
| 64 | 2 | |
| 60 | 1 | |
| 48 | 1 | |
| 32 | 4 | |
| 18 | 1 | |
| 16 | 6 | 3 |
| 8 | 1 | 4 |
| 4 | 2 | 1 |
| 2 | 1 | |

* See section 2.9.3 for the details.

**Table D3** Operating systems in use*.

| Operating systems | Mail survey* No. | Interviews* No. |
|---|---|---|
| Windows 98 | 13 | 4 (25%) |
| Windows 98 & MSDOS 6.0 | 2 | |
| | 15 (30%) | |
| Windows 97 | 3 | |
| Widows 97 & MSDOS 6.22 | 1 | |
| | 4 (8%) | |
| Windows 95 | 13 | |
| Windows 95 & MSDOS 6.22 | 2 | 12 (75%) |
| Windows 95 & MSDOS 2.22 | 1 | |
| Windows 95 & MSDOS 1.2 | 1 | |
| | 17 (34%) | |
| Windows 3.11 | 8 | |
| Windows 3.11 & MSDOS 6.22 | 2 | |
| | 12 (24%) | |
| MSDOS 3.5 | 1 | |
| MSDOS 3.3 | 1 | |
| | 2 (4%) | |

* See section 2.9.3 for the details.

# APPENDIX E*

## Questionnaire

The questionnaire asks you about the use of POSOP as a decision support tool for rice disease diagnosis and management and your opinions and information about POSOP and expert systems in general. Your opinions and information will be extremely valuable in improving POSOP and developing expert systems in other areas that might be useful in the future.

**All data provided will be kept in strictest confidence and used for improving POSOP, and as guidelines on developing other expert systems.**

### General Instructions

In the questionnaire you are asked to indicate, on a five-point scale, the extent of agreement between the attitude expressed in each statement and your own personal feeling. **The five-point scale** is:

| | | |
|---|---|---|
| 0 | indicates | *strongly disagree* |
| 1 | indicates | *disagree* |
| 2 | indicates | *undecided* |
| 3 | indicates | *agree* |
| 4 | indicates | *strongly agree* |

Draw a circle around the number which best indicates how closely you agree or disagree with the attitude expressed in each statement. For example, if you were asked:

| | | | | | |
|---|---|---|---|---|---|
| The weather in Thailand is good. | 0 | 1 | 2 | 3 | 4 |

If you ***strongly agree*** with this statement you would circle as follows.

| | | | | | |
|---|---|---|---|---|---|
| The weather in Thailand is good. | 0 | 1 | 2 | 3 | 4 |

* See section 6.4.3 for details.

You will also be using a rating scale with **likely - unlikely** as end-points. For example, if you were asked to rate '*The weather in Thailand is hot in April*' on such a scale, it would appear as follows:

The weather in Thailand is hot in April

unlikely ________:________:________:________:________ likely

very quite neither quite very

If you think that it is ***very likely*** that the weather in Thailand is very hot in April, you would make your mark as follows:

The weather in Thailand is hot in April

unlikely________:________:________:________: ___x___ likely

very quite neither quite very

In making your rating please remember the following points:

(1) In the **likely-unlikely scale**, please place your mark in the middle of spaces, not on the boundaries:

(2) In the **five-point scale**, please draw a circle around the number that corresponds closely with your opinions and be sure you answer all items.

**(3)** Please **do not omit** any item as this will affect the research results and **never put more than one mark or one circle on single scale.**

## QUESTIONNAIRE

I. If readily available would you intend to use POSOP as a decision support tool for rice disease diagnosis and management:

likely ________: ________: ________: ________: ________unlikely
very quite neither quite very

| A. Attitudes towards use of POSOP | Strongly Disagree | Disagree | Undecided | Agree | Strongly Agree |
|---|---|---|---|---|---|
| 1. If I could recommend the farmer timely rice disease control the farmer would find this extremely valuable. | 0 | 1 | 2 | 3 | 4 |
| 2. My using POSOP would be a convenient way to help me obtain information on rice disease diagnosis and management. | 0 | 1 | 2 | 3 | 4 |
| 3. My using POSOP would confuse my understanding of rice disease diagnosis and management. | 0 | 1 | 2 | 3 | 4 |
| 4. My using POSOP would help enhance my extension work efficiency. | 0 | 1 | 2 | 3 | 4 |
| 5. Introducing POSOP to agricultural extension would be wasteful of time. | 0 | 1 | 2 | 3 | 4 |
| 6. Obtaining information more easily and conveniently on rice disease diagnosis and management would be beneficial to me. | 0 | 1 | 2 | 3 | 4 |
| 7. My using POSOP would enhance my knowledge and skills in rice disease diagnosis and management. | 0 | 1 | 2 | 3 | 4 |
| 8. Having more confidence in giving advice on rice disease diagnosis and management would be good for me. | 0 | 1 | 2 | 3 | 4 |
| 9. If I could help the farmer make faster decisions in rice disease management the farmer would find this extremely valuable. | 0 | 1 | 2 | 3 | 4 |

| | Strongly Disagree | Disagree | Undecided | Agree | Strongly Agree |
|---|---|---|---|---|---|
| 10. Enhancing current extension work efficiency would be valuable to me. | 0 | 1 | 2 | 3 | 4 |
| 11. Introducing POSOP would de-emphasise my role in rice disease diagnosis and management. | 0 | 1 | 2 | 3 | 4 |
| 12. My use of POSOP as a decision support tool for rice disease diagnosis and management will be useful. | 0 | 1 | 2 | 3 | 4 |
| 13. My using POSOP would help me have more confidence in giving advice on rice disease diagnosis and management. | 0 | 1 | 2 | 3 | 4 |
| 14. My using POSOP would help me save time searching for information in rice disease diagnosis and management. | 0 | 1 | 2 | 3 | 4 |
| 15. Generally speaking, I want to do what my farmers think I should do. | 0 | 1 | 2 | 3 | 4 |
| 16. If most people who are important to me think I should use POSOP as a decision support tool in rice disease diagnosis and management, then I will use it. | 0 | 1 | 2 | 3 | 4 |
| 17. Generally speaking, I want to do what my peers think I should do. | 0 | 1 | 2 | 3 | 4 |
| 18. Generally speaking, I want to do what my organisation thinks I should do. | 0 | 1 | 2 | 3 | 4 |
| 19. My farmers will think I should use POSOP as a decision support tool. | 0 | 1 | 2 | 3 | 4 |
| 20. My organisation would think I should use POSOP as a decision support tool. | 0 | 1 | 2 | 3 | 4 |
| 21. My peers will think I should use POSOP as a decision support tool. | 0 | 1 | 2 | 3 | 4 |
| 22. It is important that I have a useful decision support tools for rice disease diagnosis and management | 0 | 1 | 2 | 3 | 4 |
| 23. I'm in favour of using POSOP as a decision support tool for rice disease diagnosis and management. | 0 | 1 | 2 | 3 | 4 |

| B. Knowledge and skills | Strongly Disagree | Disagree | Undecided | Agree | Strongly Agree |
|---|---|---|---|---|---|
| 1. I have poor computer skills. | 0 | 1 | 2 | 3 | 4 |
| 2. If my organisation funded POSOP this would be beneficial. | 0 | 1 | 2 | 3 | 4 |
| 3. Having sufficient knowledge of rice disease diagnosis and management to make my own decisions would not be easy. | 0 | 1 | 2 | 3 | 4 |
| 4. I would probably have difficulty in using POSOP. | 0 | 1 | 2 | 3 | 4 |
| 5. If I had to use POSOP at my expense this would still be worthwhile. | 0 | 1 | 2 | 3 | 4 |
| 6. Using or operating a computer would probably be difficult. | 0 | 1 | 2 | 3 | 4 |
| 7. I have a sufficient number of computers in my office to make good use of POSOP. | 0 | 1 | 2 | 3 | 4 |
| 8. Obtaining timely information on rice disease diagnosis and management from other sources would be easier than using POSOP. | 0 | 1 | 2 | 3 | 4 |
| 9. Having a greater number of computers in my office would be useful. | 0 | 1 | 2 | 3 | 4 |
| 10. Having higher capacity computers in my office would be useless. | 0 | 1 | 2 | 3 | 4 |
| 11. I can easily obtain information on rice disease diagnosis and management from other sources. | 0 | 1 | 2 | 3 | 4 |
| 12. The costs of using POSOP might be expensive. | 0 | 1 | 2 | 3 | 4 |
| 13. I have high capacity computers in my office. | 0 | 1 | 2 | 3 | 4 |
| 14. Using POSOP would probably be difficult. | 0 | 1 | 2 | 3 | 4 |
| 15. Having training on how to use POSOP would be beneficial. | 0 | 1 | 2 | 3 | 4 |

### C. Attitudes towards POSOP's features

In each following item, please draw **only a circle** around the number which best indicates how closely you agree or disagree with the attitude expressed in each statement AND **rate** the importance of each item on a five-point scale. The five-point scale is:

| | | |
|---|---|---|
| 1 | = | least important |
| 2 | = | less important |
| 3 | = | moderate important |
| 4 | = | very important |
| 5 | = | most important |

| | Strongly Disagree | Disagree | Undecided | Agree | Strongly Agree | Importance (W) |
|---|---|---|---|---|---|---|
| 1. POSOP's value as a decision support tool for rice disease diagnosis and management is high. | 0 | 1 | 2 | 3 | 4 | |
| 2. POSOP's expert (s) is/are credible. | 0 | 1 | 2 | 3 | 4 | |
| 3. POSOP's advice is applicable. | 0 | 1 | 2 | 3 | 4 | |
| 4. POSOP's user interface is good. | 0 | 1 | 2 | 3 | 4 | |
| 5. Wording used in POSOP is clear. | 0 | 1 | 2 | 3 | 4 | |
| 6. POSOP's diagnosis and advice are accurate and reliable. | 0 | 1 | 2 | 3 | 4 | |
| 7. Photos composed in POSOP are informative. | 0 | 1 | 2 | 3 | 4 | |
| 8. Photo size used in POSOP is appropriate. | 0 | 1 | 2 | 3 | 4 | |
| 9. Photos used in POSOP are clear enough | 0 | 1 | 2 | 3 | 4 | |
| 10. Font type used in POSOP is appropriate. | 0 | 1 | 2 | 3 | 4 | |
| 11. Font size used in POSOP is appropriate. | 0 | 1 | 2 | 3 | 4 | |
| 12. Font colour used in POSOP is appropriate. | 0 | 1 | 2 | 3 | 4 | |
| 13. Background colour in POSOP is appropriate. | 0 | 1 | 2 | 3 | 4 | |

**D. Opinions about POSOP and expert systems in general. Please give a full written answer to the following questionnaire in the spaces provided.**

1. What are the good features of POSOP?

..............................................................................................................

..............................................................................................................

..............................................................................................................

2. What are the bad features of POSOP?

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..............................................................................................................

..............................................................................................................

3. How could POSOP be improved?

..............................................................................................................

..............................................................................................................

..............................................................................................................

4. How could the screen design be improved?

..............................................................................................................

..............................................................................................................

..............................................................................................................

5. If POSOP does not consider all relevant factors, what is missing?

..............................................................................................................

..............................................................................................................

..............................................................................................................

**Item no. 6 –13 please tick in a box and give your reasons**

6. Does POSOP operate fast enough for you?

☐ Yes ☐ No

7 (a) How often would you use POSOP in a year? Please specify.......................time(s).

7 (b) Which months would you use POSOP? Please tick. You can choose more than one.

| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Jan | Feb | Mar | April | May | June | July | Aug | Sept | Oct | Nov | Dec |

8. Why would you use POSOP? Please give your reasons.

☐ Yes..........................................................................................

.................................................................................................

.................................................................................................

☐ No..........................................................................................

.................................................................................................

.................................................................................................

9.Would you use POSOP in the office after visiting a farmer and report back the next day? Please give your reasons.

☐ Yes..........................................................................................

.................................................................................................

.................................................................................................

☐ No..........................................................................................

.................................................................................................

.................................................................................................

10. Would you use POSOP with a farmer beside you? Please give your reasons.

☐ Yes..........................................................................................

.................................................................................................

.................................................................................................

☐ No..........................................................................................

.................................................................................................

.................................................................................................

11. Would you use POSOP to train yourself in rice disease diagnostic skills? Please give your reasons.

☐ Yes..........................................................................................

.................................................................................................

.................................................................................................

☐ No..........................................................................................

.................................................................................................

.................................................................................................

12. Should your office support the development of many more expert systems? Please give your reasons.

☐ Yes………………………………………………………………………………………

……………………………………………………………………………………………

……………………………………………………………………………………………

☐ No………………………………………………………………………………………

……………………………………………………………………………………………

……………………………………………………………………………………………

13. Do you a think a wide range of well prepared expert systems have a potential for helping extension officers? Please give your reasons.

☐ Yes………………………………………………………………………………………

……………………………………………………………………………………………

……………………………………………………………………………………………

☐ No………………………………………………………………………………………

……………………………………………………………………………………………

……………………………………………………………………………………………

14. How many times in a year would farmers ask you to deal with rice disease problems? Please specify number of time(s)…………………

15. Please list the other areas you would expect an expert system to be valuable.

……………………………………………………………………………………………

……………………………………………………………………………………………

……………………………………………………………………………………………

**E. General Information:**

1. Sex ☐ Male ☐ Female

2. Age __________ years

3. Years of experience as an extension agent __________ years

4.1 Vocational Grade Point Average (GPA)* __________

4.2 Major ______________________ 4.3Institution ____________________________

5.1 Bachelor Grade Point Average (GPA)* __________

5.2 Major ______________________ 5.3 Institution ____________________________

6.1 Master Grade Point Average (GPA)* __________

6.2 Major ______________________ 6.3Institution ____________________________

**Note:** * If your GPA is in percent, please fill in percent.

## APPENDIX F

# Opinions

**Table F1** Opinions about POSOP' s good features*.

| Opinions | Number of responses |
|---|---|
| Easy and convenient to use. | 50 |
| Quick diagnosis and Timely decision support. | 20 |
| Easy to understand. | 14 |
| Clear pictures and text. | 13 |
| Accuracy and credibility of diagnosis. | 7 |
| Providing users with a wide-range of knowledge, skills, ideas, and all the information needed in rice diseases and management. | 7 |
| Explanation facilities. | 6 |
| Clear and concise wordings. | 4 |
| Does not need basic computer skills and farmers can use. | 4 |
| Demonstrating a really good knowledge base. | 3 |
| A good, useful, and up-to-date tool for rice disease diagnosis. | 3 |
| Good system structure concepts. | 2 |
| In Thai language. | 2 |
| Easy to keep. | 1 |
| Problems solving. | 1 |

* See section 6.6.1.1 for details.

**Table F2** Opinions about POSOP' s bad features*.

| Opinions | Number of responses |
|---|---|
| A computer is required. | 5 |
| Some information needed further explanation. | 10 |
| More diseases need to be covered. | 4 |
| Some symptom descriptions were not clear. | 2 |
| Pest and storage insects, and natural predators needed to be covered. | 3 |
| Dealing with only one crop. | 3 |
| Not yet covered all farmers' practices. | 1 |
| Too little diagnostic content. | 1 |
| Some rice cultivars were not up-to-date. | 1 |
| Causal organism names are in English. | 1 |
| It might be expensive and could not afford it. | 1 |
| Not yet distributed for sale. | 1 |
| Not convenient to use as there is a big gap between developer and users. | 1 |
| Some pictures displayed were a bit too small. | 8 |
| More variety of sample pictures is needed. | 3 |
| Some pictures were not so clear. | 1 |
| Text was a bit too small. | 1 |
| Darker text colour is needed. | 1 |
| Users needed some basic computer skills. | 1 |
| A button to go back to the previous screen is needed. | 1 |
| All input data should be displayed on the screen to let users review the input data before diagnosis. | 1 |
| Getting confused. | 1 |
| Cannot print. | 1 |
| Some sound effects are needed. | 1 |

* See section 6.6.1.1 for details.

**Table F3** The reasons for using POSOP*.

| **Reasons** | **Number of responses** |
|---|---|
| An easy and convenient way to obtain information or solutions. | 28 |
| It quickly provided diagnosis or analysis. | 22 |
| Rice was the main crop in their areas of responsibility and farmers often asked for advice. | 20 |
| Being a decision support or diagnostic tool. | 20 |
| Credibility and accuracy of its diagnosis. | 12 |
| Ease of diagnosing and understanding the problem. | 11 |
| Very useful and necessary for farmers and themselves. | 9 |
| Saving their time searching for information and providing timely solutions. | 7 |
| Enhancing their knowledge for the development of their extension work. | 5 |
| New technology that is necessary and useful for up-to-date extension services. | 4 |
| Its explanation facilities and pictures displayed answered farmers' problems. | 4 |

* See section 6.6.1.1 for details.

**Table F4** The reasons for not using POSOP*.

| Reasons | Number of responses |
|---|---|
| No computer available, or the ones available were old models. | 5 |
| Don't know how to operate a computer. | 1 |
| No supporting budget. | 1 |
| Already having adequate knowledge to diagnose the diseases and make their own decisions. | 3 |
| Their areas of responsibility were not rice production areas. | 2 |
| The research has not yet been approved. | 1 |

* See section 6.6.1.1 for details.

**Table F5** The reasons for using POSOP to train themselves in rice disease diagnostic skills*.

| Reasons | Number of responses |
|---|---|
| Building or increasing confidence in accurate and credible diagnosis. | 27 |
| Gain more diagnostic experience, knowledge and skills. | 14 |
| Preparing information to be ready to answer farmers' questions. | 11 |
| Developing quick diagnostic skills. | 11 |
| Very useful for speeding up extension services. | 9 |
| As a knowledge reminder or refresher. | 8 |
| A more convenient way to search for information rather than searching in textbooks. | 8 |
| Being an easy and convenient way to acquire knowledge and to develop their expertise to expert level. | 7 |
| Double check their diagnoses. | 6 |
| To study the diagnostic process of the system that might be applicable to other cereal crops. | 3 |

* See section 6.6.1.1 for details.

**Table F6** The reasons for using POSOP with a farmer*.

| **Reasons** | **Number of responses** |
|---|---|
| To learn, diagnose, discuss, and decide together. | 17 |
| Farmers could see with their own eyes how extension agents diagnose the diseases. | 15 |
| Increasing farmer's confidence in obtaining correct and credible information. | 10 |
| To train and guide farmers how to use POSOP so that they can help themselves in the future. Farmers could learn and develop their own knowledge in rice disease diagnosis. | 8 |
| Farmers could compare the symptoms found in the field with the pictures displayed in POSOP for increasing accuracy and confidence in diagnosis, as farmers knew the symptoms best. | 8 |
| Gain credibility from their farmers. | 7 |
| Wanting farmers to see the importance of the accuracy, quickness, and convenience of POSOP to their career, and to see advanced technology which farmers need to get used to and to become aware of computer technology. | 6 |

* See section 6.6.1.1 for details.

**Table F7** The reasons a wide range of well-prepared expert systems had potential to help extension agents*.

| Reasons | Number of responses |
|---|---|
| Enhancing their knowledge, skills, ideas, vision, efficiency, potential, and performance in problem solving. | 22 |
| Being a very useful and up-to-date knowledge base or information source as decision support tools for better decisions. | 22 |
| Saving their time searching for information and helping make faster decisions and provide timely solutions for farmers. | 22 |
| Being a very good, useful, and newly applicable technology that is necessary for facilitating, supporting, and increasing their extension work efficiency. | 12 |
| They believed that they were not specialists and lacked expertise whereas experts did research and studied from real world situations, and had vast experience in particular problem areas which could be shared. The knowledge base in expert systems, being based on experts' knowledge and experiences, were validated; and, therefore, they could make use of experts' expertises through the expert systems. | 10 |
| In case the agents were not available, others in their office could use the systems to obtain the information needed. | 10 |
| Building or increasing their confidence in giving advice. | 6 |
| A convenient way to obtain information. | 6 |
| The systems could be developed in many other areas. | 5 |

* See section 6.6.1.1 for details.

**Table F8** The reasons for supporting the development of many more expert systems*.

| Reasons | Number of responses |
|---|---|
| Being very useful for farmers. | 20 |
| Being very useful for themselves. | 15 |
| Saving their time searching for information, and providing faster and timely solutions. | 14 |
| Enhancing their knowledge, skills, efficiency, and performance. | 12 |
| Being an up-to-date variety knowledge base (or storage brain) for District Agricultural Extension Office's use. | 12 |
| Being a convenient way to obtain the information needed. | 5 |
| Being a good diagnostic tool. | 4 |
| Developing their offices' potential and gaining credibility for both themselves and their offices from the general public. | 3 |
| Being a knowledge exchange agent that bridges the knowledge gap within the same office. | 2 |
| Helping them make decisions with confidence. | 2 |
| Speed up and support their extension work. | 2 |
| In case that they were not available, anyone could use the systems to obtain the information needed. | 2 |
| Currently, few systems were available. | 1 |

* See section 6.6.1.1 for details.

# APPENDIX G
# POSOP

## 1. Introduction

POSOP (named after the Goddess of Rice) is an interactive expert system designed to operate under the Windows operating system. There is both a Thai and English version. The objective is to provide the user with a means to diagnose rice diseases and provide treatment suggestion. The sections that follow give examples of the screens a user will encounter.

## 2. POSOP Description

**Important Rice Diseases in Thailand diagnosed by POSOP***

| Disease | Causal organism |
|---|---|
| Blast | **Pyricularia oryzae** |
| Narrow Brown Spot | *Cercospora oryzae* |
| Brown Spot | *Helminthosporium oryzae* |
| Sheath Blight | *Rhizoctonia solani* |
| Bakanae | *Fusarium moniliforme* |
| Sheath Rot | *Acrocylindrium oryzae* *(Sarocladium oryzae)* |
| False Smut | *Ustilaginoidea virens* |
| Dirty panicle | *Cercospora oryzae, Acrocylindrium oryzae, and Helminthosporium oryzae* |
| Bacterial Leaf Blight | *Xanthomonas oryzae* |
| Bacterial Leaf Streak | *Xanthomonas translucens f. sp. Oryzae* |
| Yellow Orange Leaf Virus | *Virus* |
| Ragged Stunt Virus | *Virus* |
| Gal Dwarf Virus | *Virus* |
| Orange Leaf Mycoplasma | *Mycoplasma* |
| Root-knot nematode | *Meloidogyne graminicola* |

* See section 2.11 for details.

### 3. Some selected screens displayed in POSOP

As expert systems and POSOP are new to extension agents, they are introduced in the initial screens as shown in Figures 1-3.

**Figure 1**

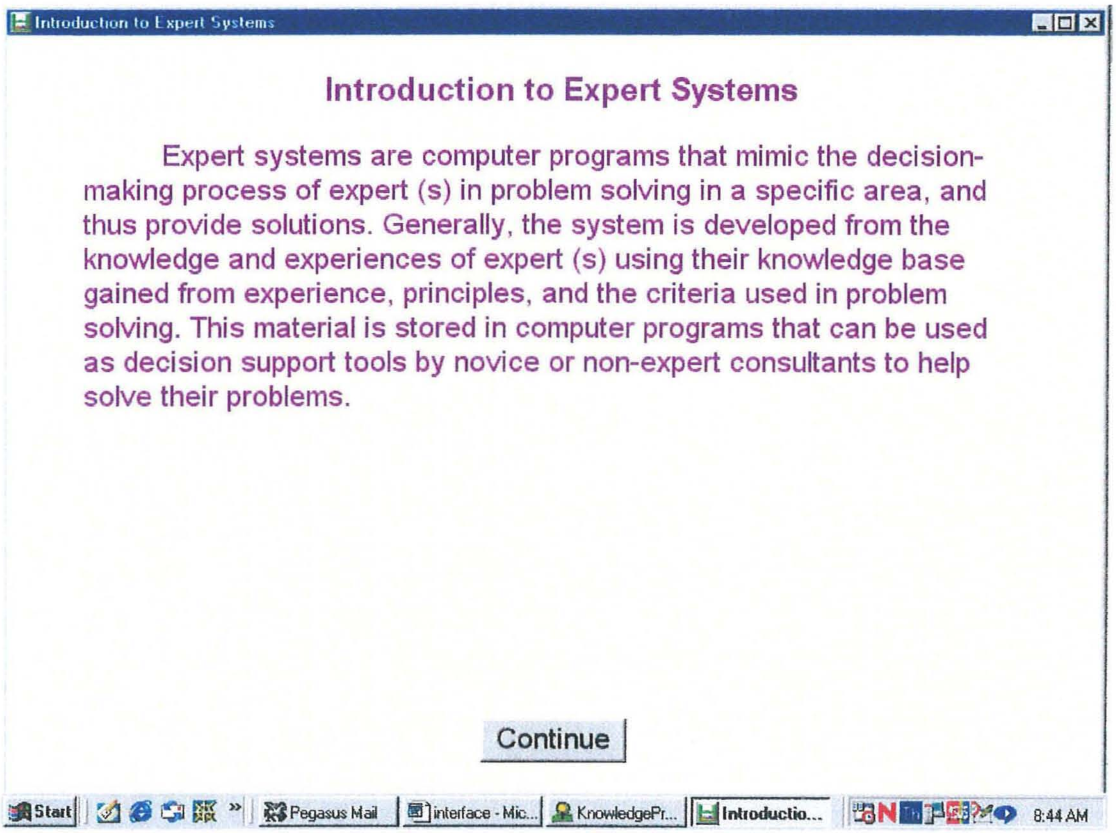


**Figure 2**

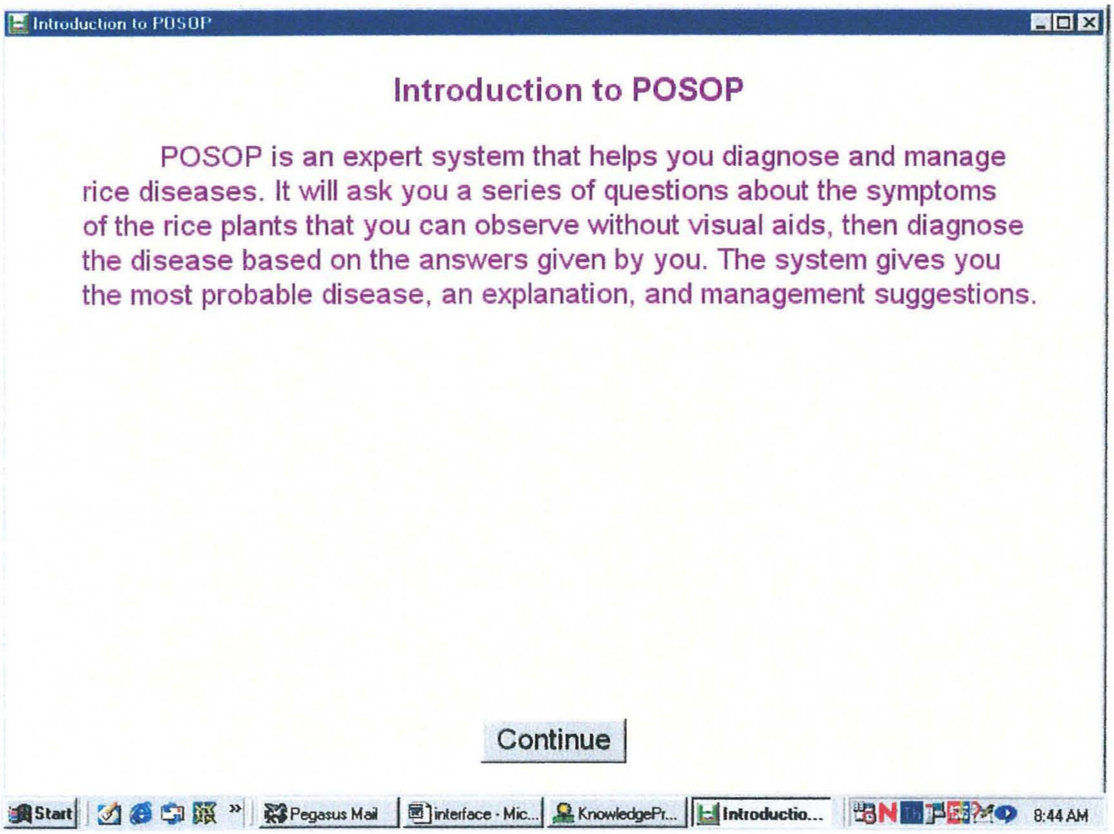
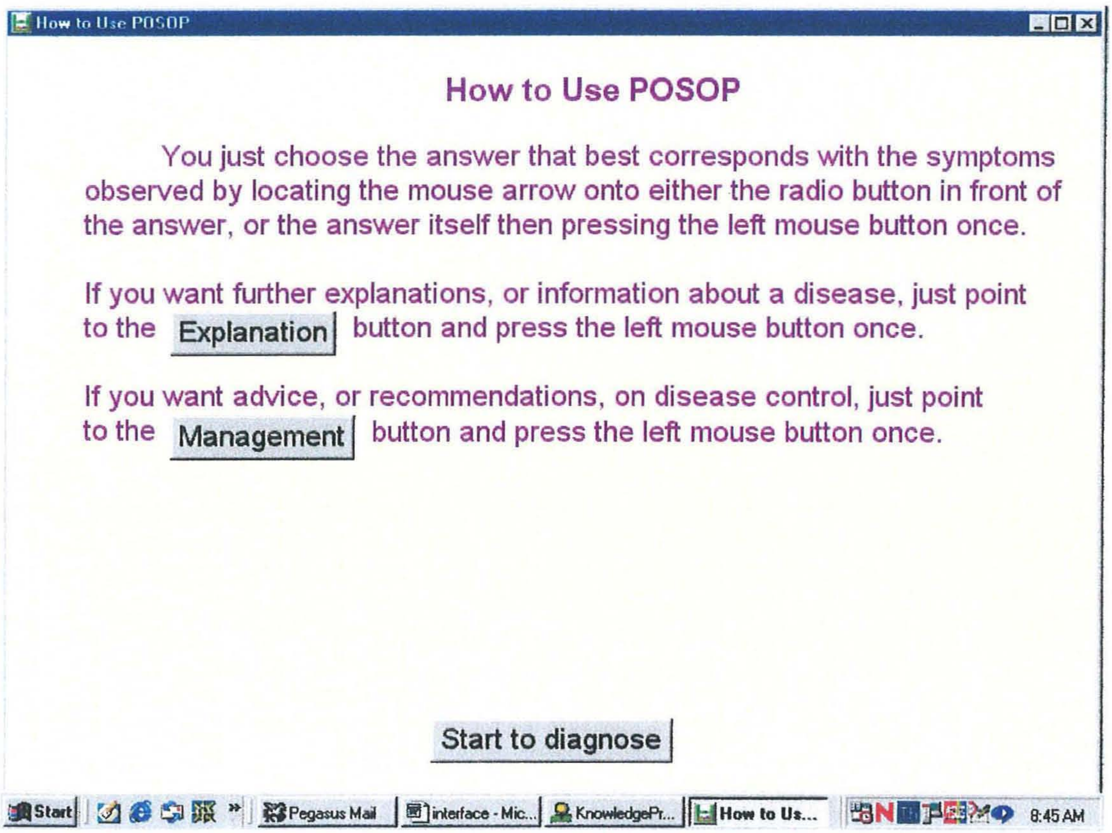
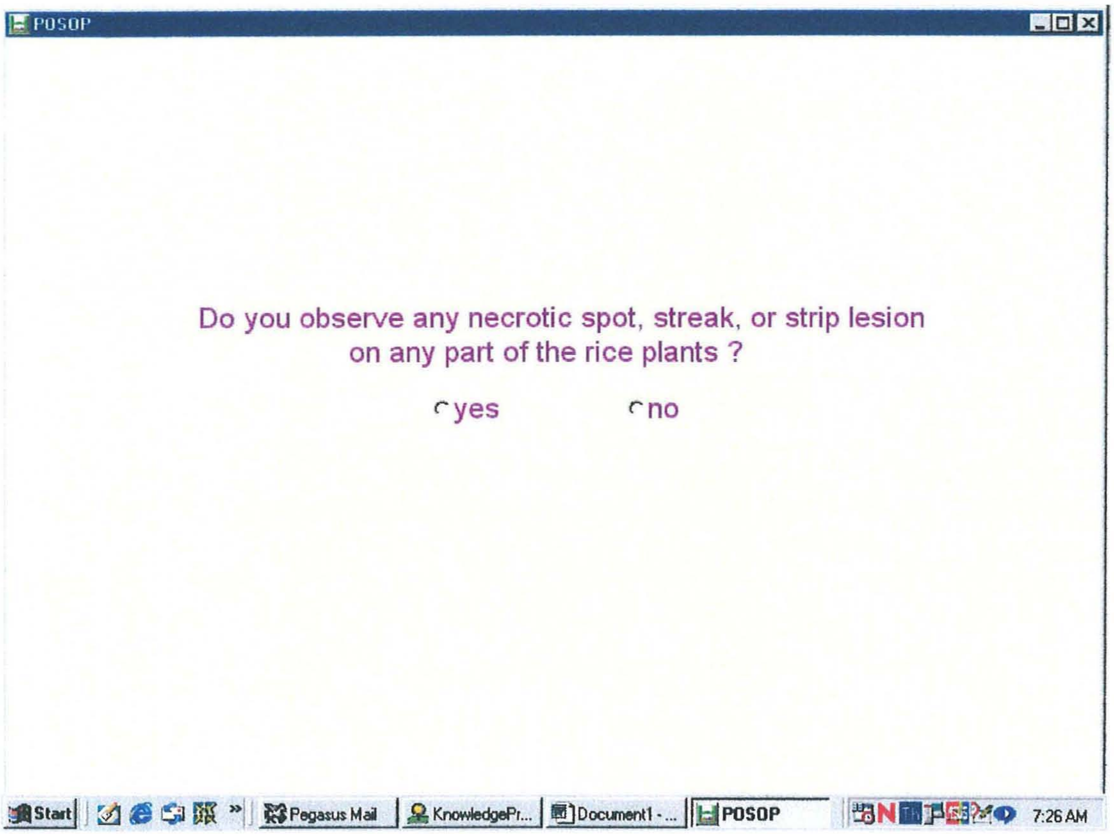



**Figure 3**



## 4. An example of a complete diagnosis session

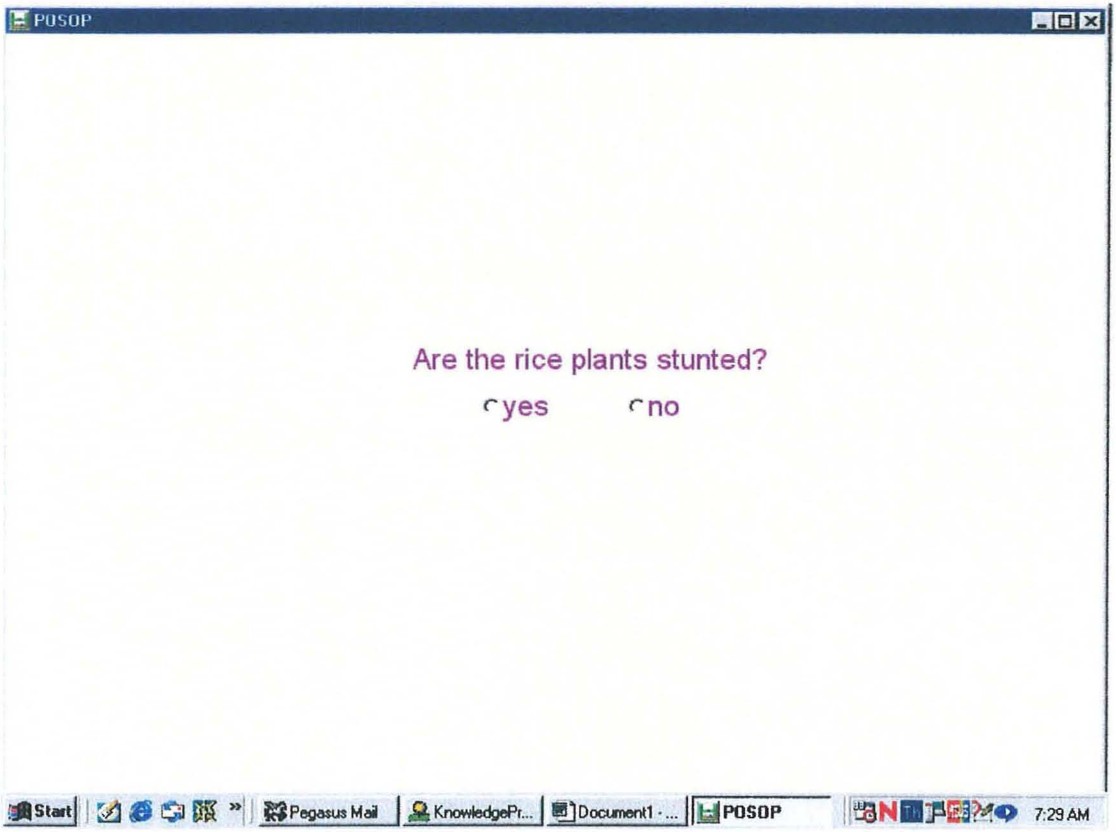
When a user clicks on the 'Start to diagnose' button, POSOP gathers information from the user by asking a series of questions according to its hypotheses. The answers given by the user are fed into the inference engine as input data.




Hypothesis: If the answer is yes, it is likely that the causal organism is a fungus. If the answer is no, it might be a rare fungus that causes different symptoms, or bacteria, mycoplasma, or virus.

Reason: Because fungi reproduce spores, once these spores spread and fall on the rice plant, they germinate and destroy the surrounding plant cells causing necrotic spots, streaks, and strip lesions.

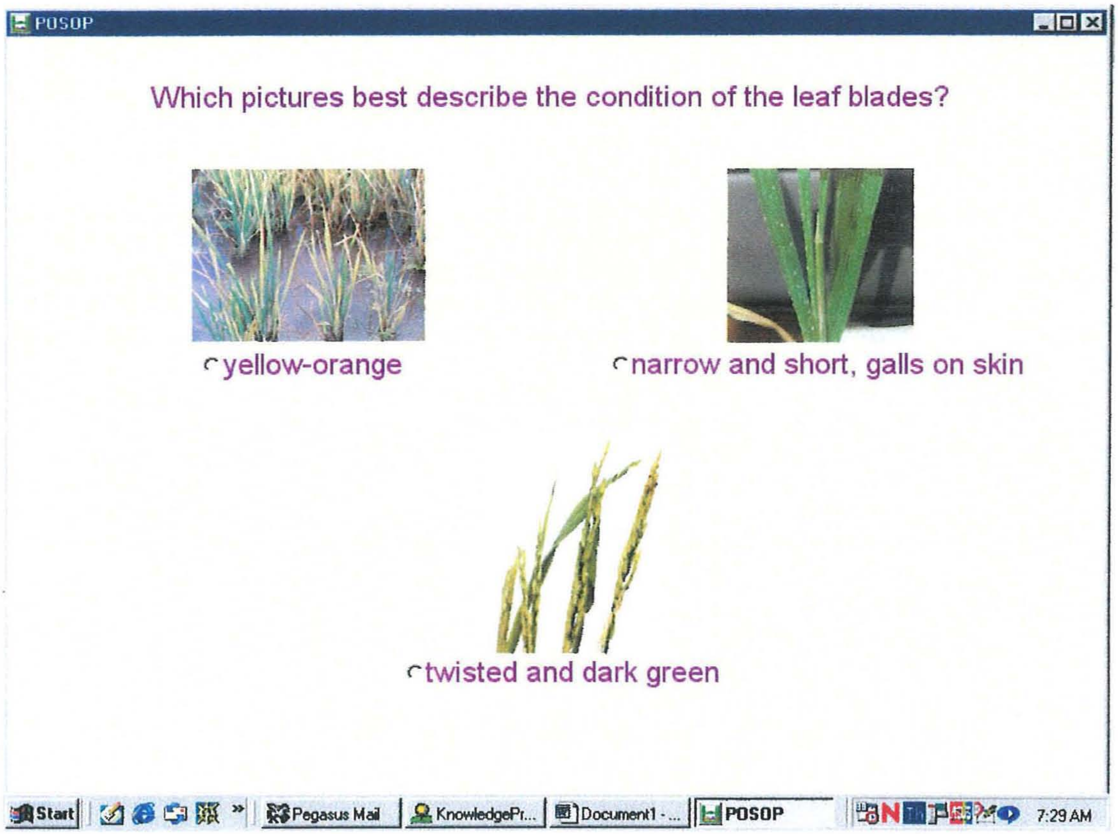
Suppose the user answers 'no. ' POSOP asks the next question.

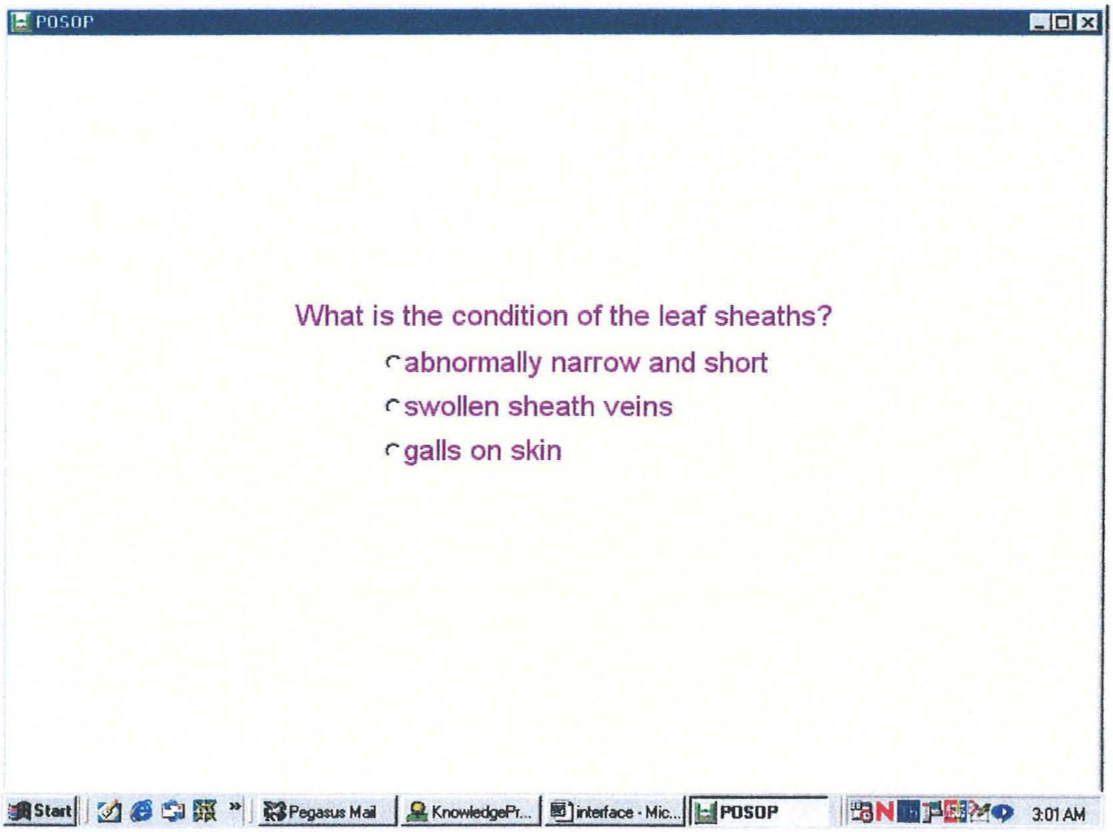


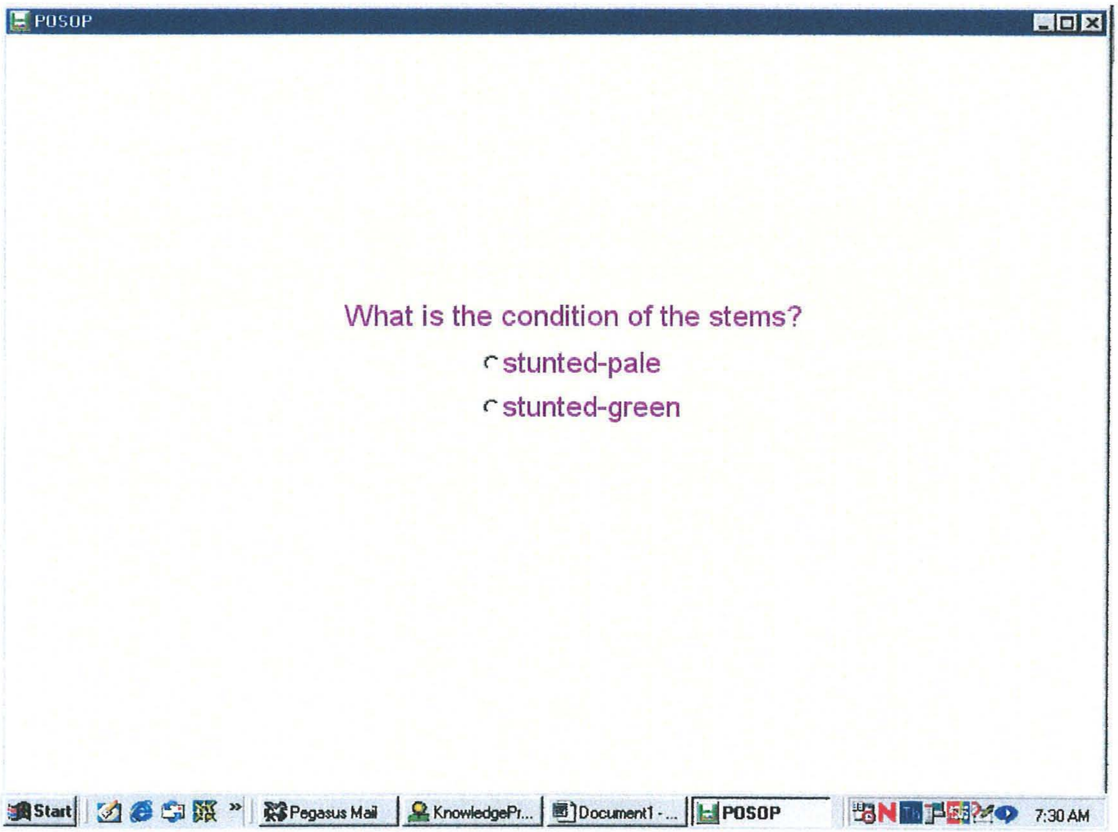

Hypothesis: If the answer is 'yes, ' it is likely that the causal organism is a virus.
If the answer is 'no,' it might be another fungi, bacteria, or mycoplasma.

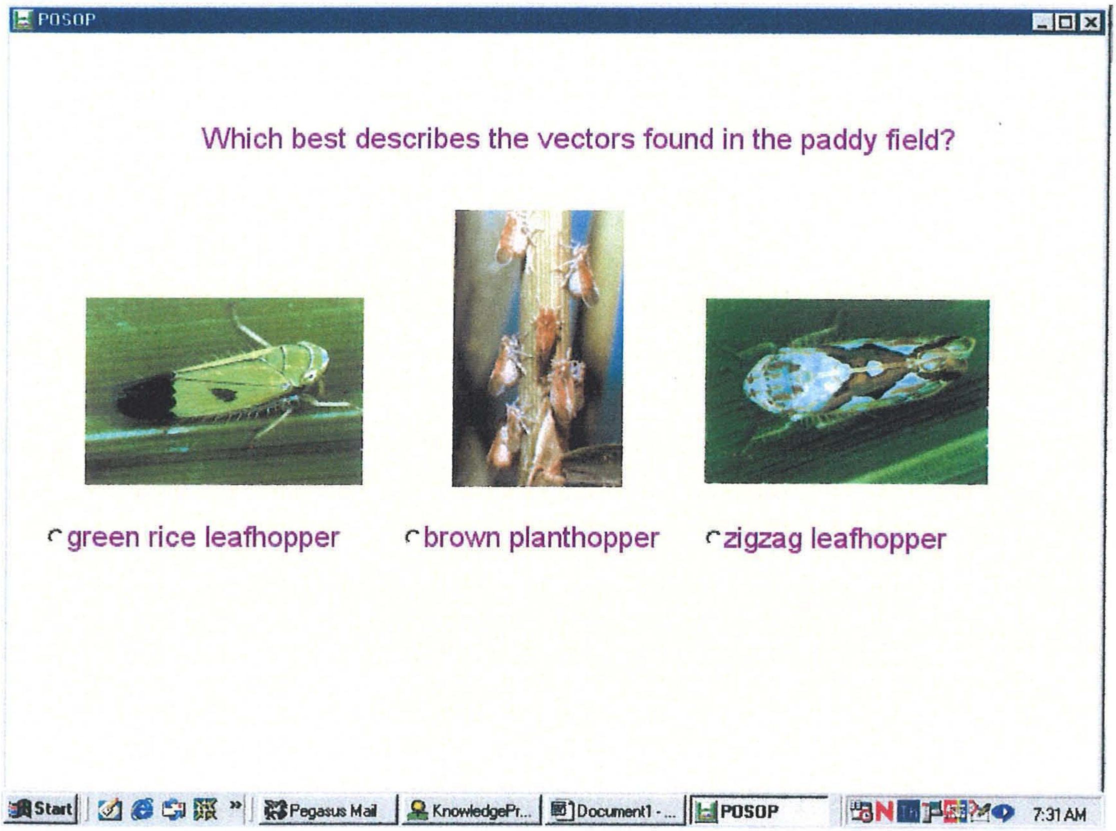
Reason: An obvious common symptom of viral diseases is stunt. However, each virus has its unique symptoms and since a virus is transmitted by insect vector (s), it is important to know the insect (s) found in the paddy field.

Suppose the user answers 'yes'. POSOP will ask for more specific information and the insect (s) found as follows.


POSOP
Which pictures best describe the condition of the leaf blades?
yellow-orange
narrow and short, galls on skin
twisted and dark green
Start
Pegasus Mail
KnowledgePr...
Document1 - ...
POSOP
7:29 AM


POSOP
What is the condition of the leaf sheaths?
abnormally narrow and short
swollen sheath veins
galls on skin
Start
Pegasus Mail
KnowledgePr...
interface - Mic...
POSOP
3:01 AM


POSOP
What is the condition of the stems?
stunted-pale
stunted-green
Start
Pegasus Mail
KnowledgePr...
Document1 - ...
POSOP
7:30 AM


POSOP
Which best describes the vectors found in the paddy field?
green rice leafhopper
brown planthopper
zigzag leafhopper
Start
Pegasus Mail
KnowledgePr...
Document1 - ...
POSOP
7:31 AM

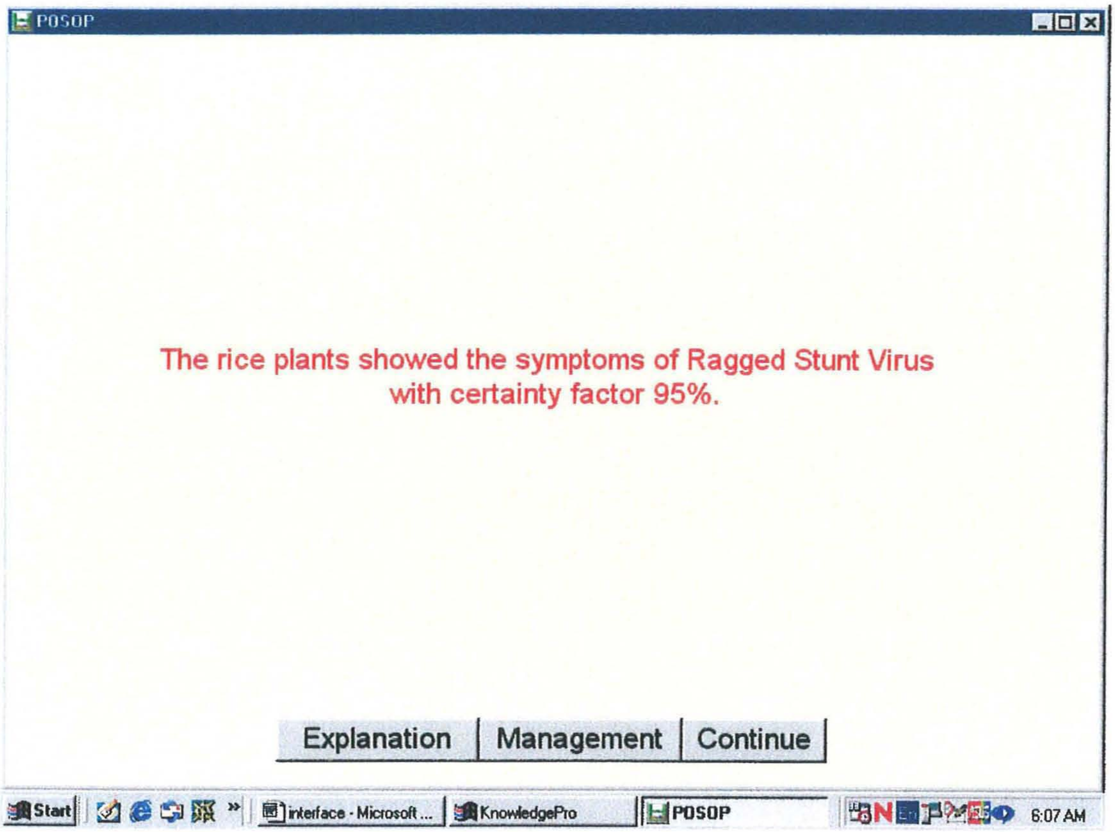
Suppose the user answers:

| | |
|---|---|
| The condition of the leaf blades: | twisted and dark green. |
| The condition of the leaf sheaths: | swollen sheath veins. |
| The condition of the stems: | stunted-green |
| The insect vector (s) found: | brown planthopper |

POSOP starts its diagnosis. The inference engine searches for the rule in POSOP' s knowledge base that matches the input data. It finds a rule stating:

IF leaf blade is twisted and dark green AND
leaf sheath has swollen sheath vein AND
stem is stunted-green AND
vector is brown planthopper
THEN the disease is ragged stunt virus. (See section 2.9.5.3)

The diagnostic result screen is displayed, and the user can obtain more information about the disease and its management by clicking on 'Explanation' and 'Management' buttons.



Ragged Stunt Virus Explanation

## Ragged Stunt Virus

Ragged Stunt Virus is not transmitted by seeds, soil, water, wind, or touching, but by the Brown Planthopper (*Nilaparvata lugens*). When the virus is sucked into the insect's body and incubated for 8 days on average, then the virus can be transmitted. While the vector is sucking cell sap, it releases the virus to the healthy plants. Two weeks to one month later, the infected plants will show the disease symptoms. The disease can occur at any stage of growth. The symptoms can appear at 15 - 30 days after infection. If the plants are infected at 15 - 45 days, serious symptoms appear. If the plants are infected at the age of 60 days or older, the symptoms are not serious.

Ragged Stunt Virus was first found in 1977 in Bahng Nam Priaw district, Chachoengsao province. Serious damage was found in the RD 7 cultivar in about 200 rais (320,000 sq.m.). In the following year, the disease was more serious and spread in many provinces in the Central Plain, especially in the Lahd Bua Luang district, Ayuthaya province, with the damaged area found over a continuous area larger than 10,000 rais (16,000,000 sq.m.). In addition, the disease was also found in Nakhon Pathom, Angtong, Suphan Buri, Pathum Thani, Uthai Thani, Chai Nat,

Start | Exploring ... | interface ... | Knowledg... | POSOP | Ragged... | 4:41 AM

Ragged Stunt Virus Explanation

damaged area found over a continuous area larger than 10,000 rais (16,000,000 sq.m.). In addition, the disease was also found in Nakhon Pathom, Angtong, Suphan Buri, Pathum Thani, Uthai Thani, Chai Nat,
Sing Buri, Nonthaburi, and Bangkok. In 1980 the disease damaged the rice crop in about 200,000 rais (320,000,000 sq.m.) and a report showed that the diseased area in Nakon Pathom province covered approximately 68,750 rais (110,000,000 sq.m.).

### Symptoms

The diseased plants are stunted, with narrow-short and dark green leaves. New leaves emerge slower than normal and are malformed after emergence. The leaf tips are twisted, causing the characteristic called "Twisted Leaf Disease." In addition, ragging of the leaf edges, and swelling of the leaf veins, appear along the leaf blades and leaf sheaths. The plants delay heading and give defective panicles. Most panicles yield empty grains and those that mature are often dirty and of low quality. The diseased crop gives about 1/3 - 2/3 of normal yield. If the disease coincides with others e.g. Dirty Panicle and Narrow Brown Leaf Spot, which often occurs, the yield can be reduced to zero.

Continue

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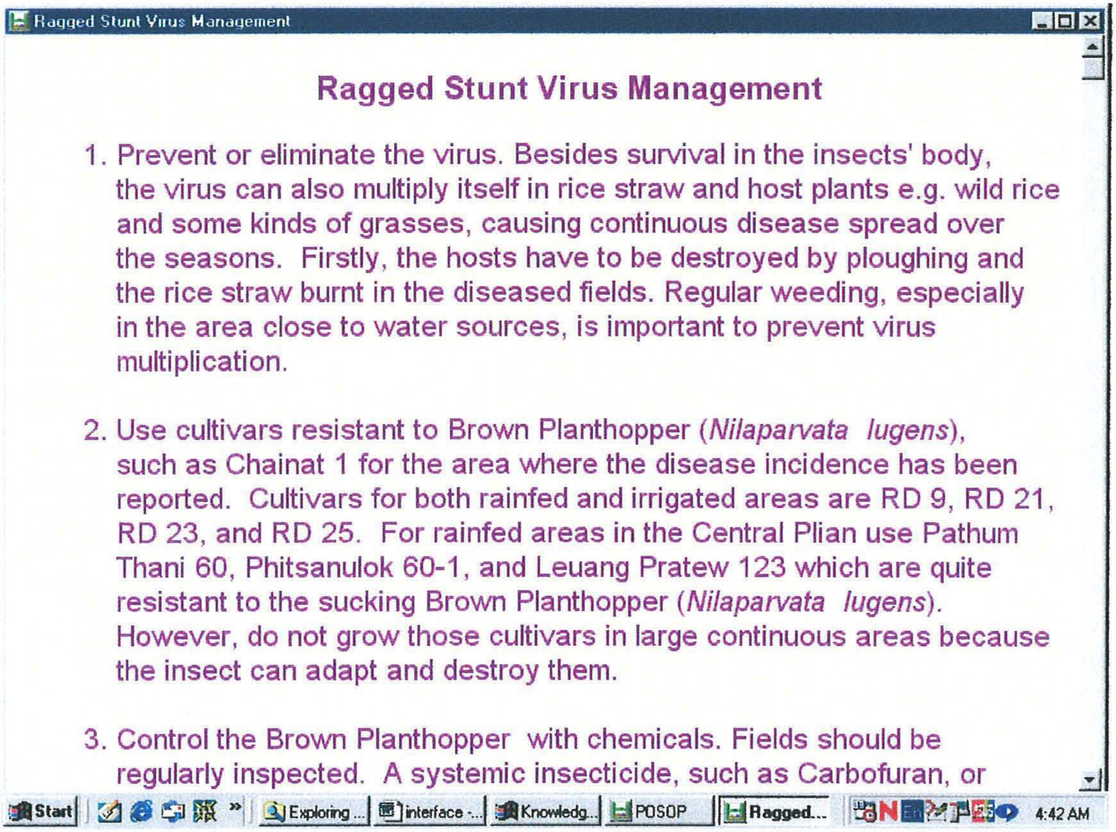


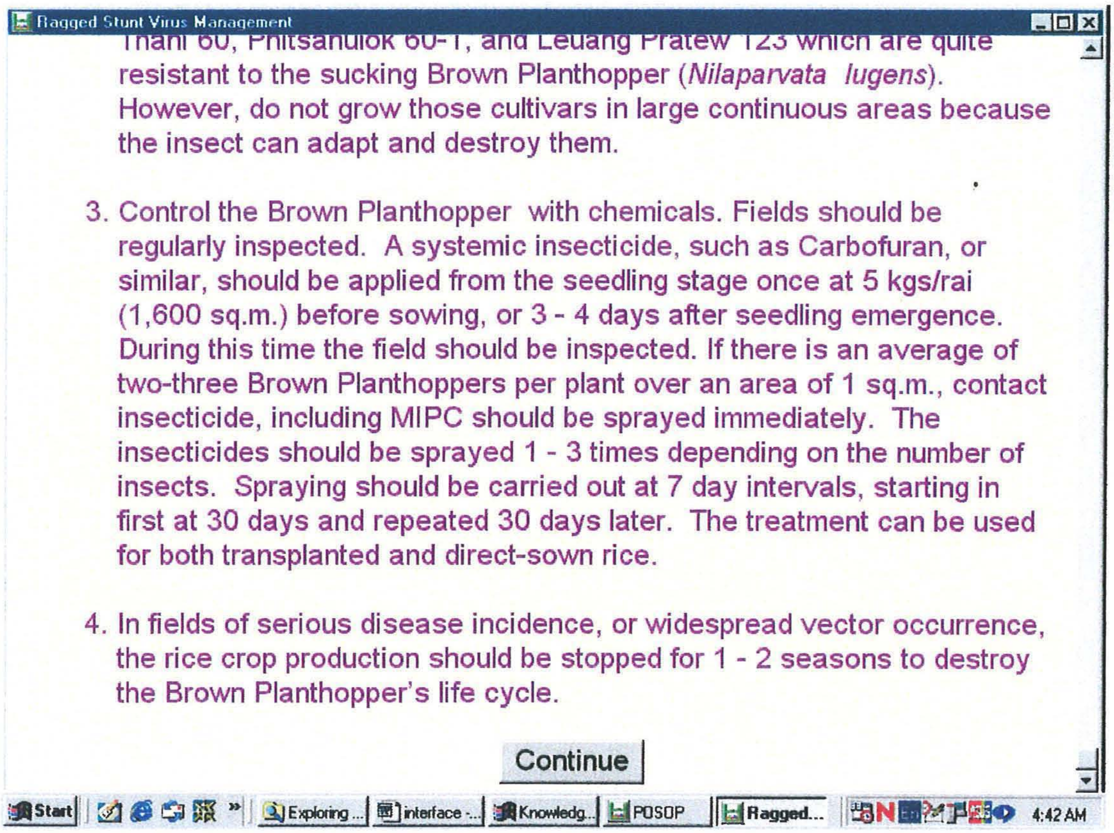
Ragged Stunt Virus Management

## Ragged Stunt Virus Management

1. Prevent or eliminate the virus. Besides survival in the insects' body, the virus can also multiply itself in rice straw and host plants e.g. wild rice and some kinds of grasses, causing continuous disease spread over the seasons. Firstly, the hosts have to be destroyed by ploughing and the rice straw burnt in the diseased fields. Regular weeding, especially in the area close to water sources, is important to prevent virus multiplication.

2. Use cultivars resistant to Brown Planthopper (*Nilaparvata lugens*), such as Chainat 1 for the area where the disease incidence has been reported. Cultivars for both rainfed and irrigated areas are RD 9, RD 21, RD 23, and RD 25. For rainfed areas in the Central Plian use Pathum Thani 60, Phitsanulok 60-1, and Leuang Pratew 123 which are quite resistant to the sucking Brown Planthopper (*Nilaparvata lugens*). However, do not grow those cultivars in large continuous areas because the insect can adapt and destroy them.

3. Control the Brown Planthopper with chemicals. Fields should be regularly inspected. A systemic insecticide, such as Carbofuran, or



Ragged Stunt Virus Management

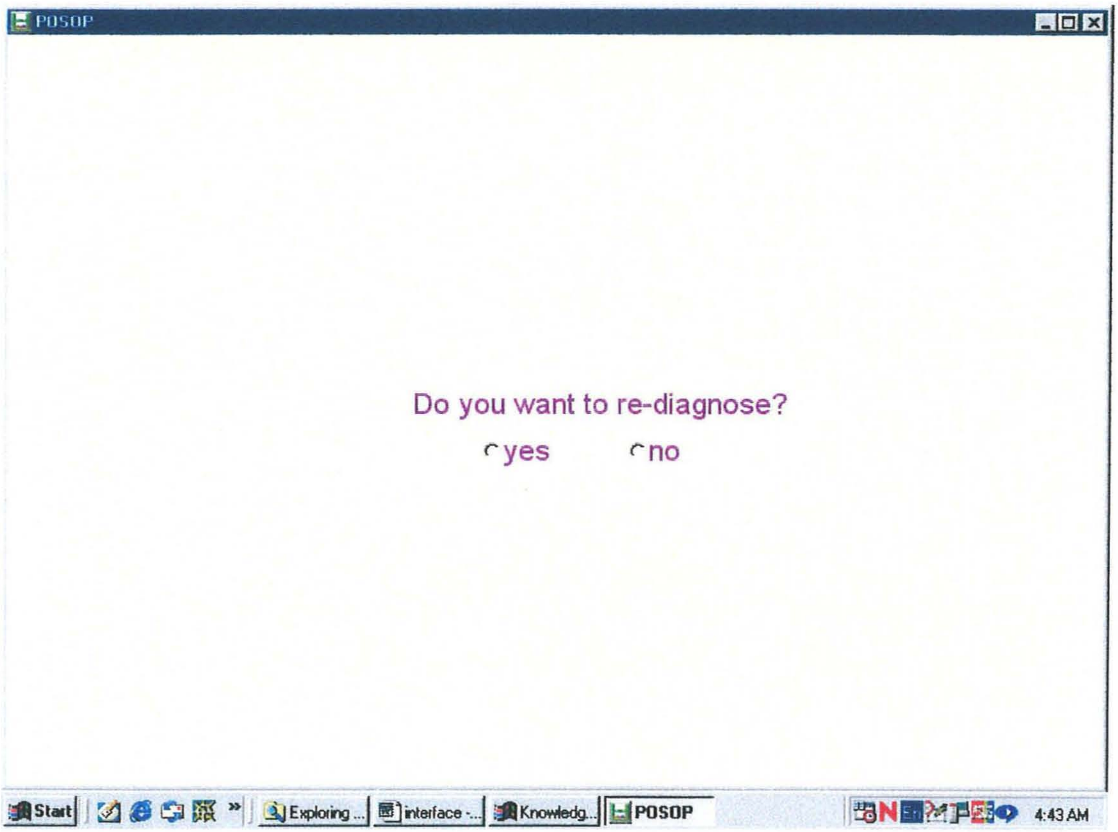
Thani 60, Phitsanulok 60-1, and Leuang Pratew 123 which are quite resistant to the sucking Brown Planthopper (*Nilaparvata lugens*). However, do not grow those cultivars in large continuous areas because the insect can adapt and destroy them.

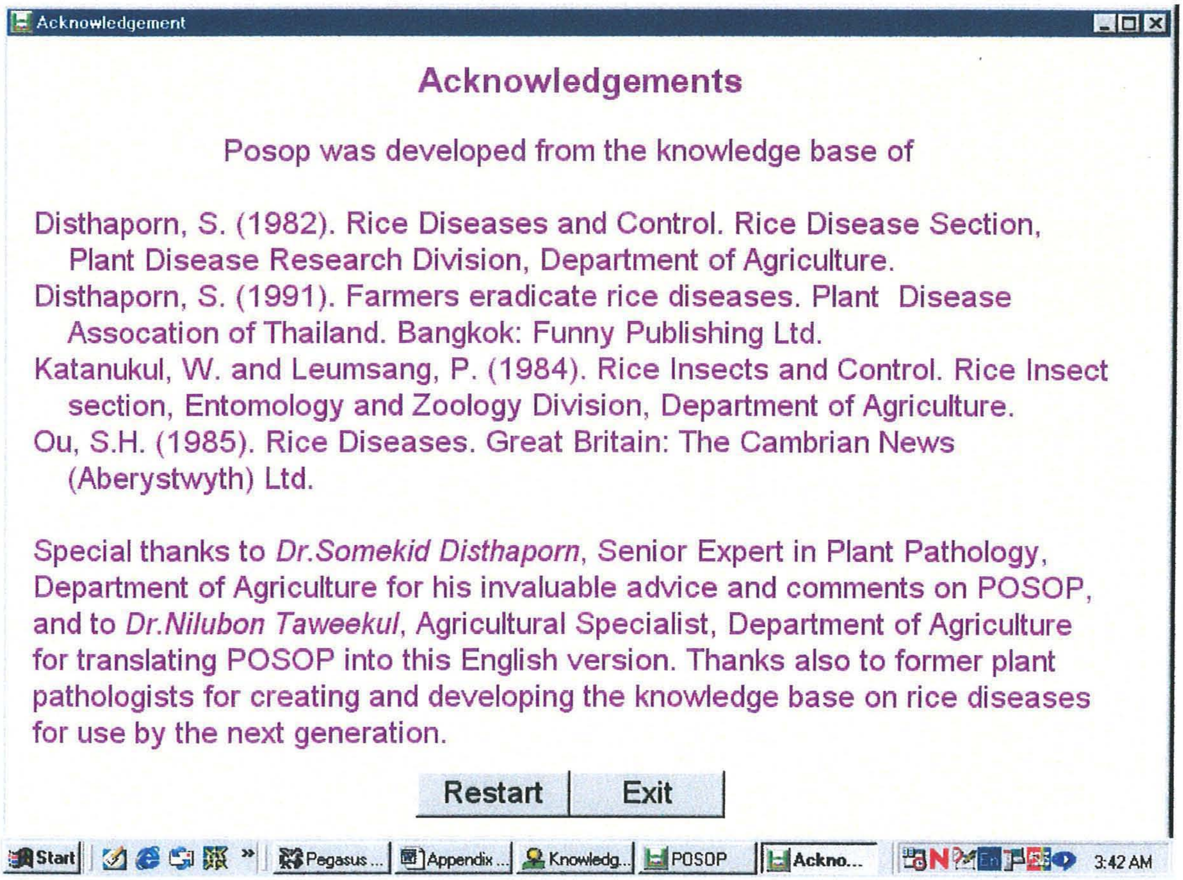
3. Control the Brown Planthopper with chemicals. Fields should be regularly inspected. A systemic insecticide, such as Carbofuran, or similar, should be applied from the seedling stage once at 5 kgs/rai (1,600 sq.m.) before sowing, or 3 - 4 days after seedling emergence. During this time the field should be inspected. If there is an average of two-three Brown Planthoppers per plant over an area of 1 sq.m., contact insecticide, including MIPC should be sprayed immediately. The insecticides should be sprayed 1 - 3 times depending on the number of insects. Spraying should be carried out at 7 day intervals, starting in first at 30 days and repeated 30 days later. The treatment can be used for both transplanted and direct-sown rice.

4. In fields of serious disease incidence, or widespread vector occurrence, the rice crop production should be stopped for 1 - 2 seasons to destroy the Brown Planthopper's life cycle.

Continue

POSOP asks whether the user wants to re-diagnose. If the user does, the diagnosis session starts again. If the user does not, the 'Acknowledgements' screen is displayed, the user can choose to exit, or restart, POSOP.




Acknowledgement
Acknowledgements
Posop was developed from the knowledge base of
Disthaporn, S. (1982). Rice Diseases and Control. Rice Disease Section, Plant Disease Research Division, Department of Agriculture.
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Katanukul, W. and Leumsang, P. (1984). Rice Insects and Control. Rice Insect section, Entomology and Zoology Division, Department of Agriculture.
Ou, S.H. (1985). Rice Diseases. Great Britain: The Cambrian News (Aberystwyth) Ltd.
Special thanks to Dr.Somekid Disthaporn, Senior Expert in Plant Pathology, Department of Agriculture for his invaluable advice and comments on POSOP, and to Dr.Nilubon Taweekul, Agricultural Specialist, Department of Agriculture for translating POSOP into this English version. Thanks also to former plant pathologists for creating and developing the knowledge base on rice diseases for use by the next generation.
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