Knowledge bases for Users' Attitudes toward ERP Systems

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Abstract

Enterprise resource planning (ERP) systems have gained much attention from both practitioners and researchers because they are generally regarded as tools to improve business efficiency and employee productivity. Previous surveys featured ERP software markets as high potential margin and intense competition. Many factors may influence business decision on ERP systems implementation where users' attitudes regarding these factors play a crucial role to the decision. ERP software vendors must design the marketing strategies in harmony with the prospective users' requirements. This study proposes a novel approach, Bayesian networks, in developing knowledge bases of users' attitudes toward ERP systems. Using the Bayesian network, the factors and their interrelationship will be modeled compactly in graphical as well as numerical levels. This work first identifies the factors influencing business decision to implement ERP systems. Second, based on these factors this study designs the questionnaire to investigate users' attitudes towards ERP systems, which are further analyzed for the foundation of the Bayesian network. Third, the structure and parameters of the Bayesian network are learned from the outcomes of the first two stages. Finally, this paper demonstrates how Bayesian networks support prediction and decision in ERP system marketing. This paper aims to propose Bayesian networks in ERP software industry, which facilitates knowledge acquisition and marketing strategy generation for enterprise systems providers.

1. Introduction

Enterprise resource planning (ERP) systems have gained much attention from both practitioners and researchers because they are generally used to improve operational efficiency as well as employee productivity. ERP software markets are normally featured by high potential margin and intense competition. However, many factors may influence business decision on ERP systems implementation where users' attitudes regarding these factors play a crucial role to the decision. ERP software vendors must design the marketing strategies in compliance with the prospective users' requirements. This study proposes a novel approach, Bayesian networks, as the knowledge bases for users' attitudes toward ERP software. Bayesian networks have been widely utilized as the knowledge bases in medicine, engineering, business, etc, whose application in enterprise systems marketing are still sparse. This study adopts a three-stage procedure in developing the knowledge bases. In the first stage, by literature review this work identifies the factors influencing business decision to implement ERP software. In the second stage, based on these factors this work designs the questionnaire to investigate users' attitudes towards ERP systems, which are further analyzed for the foundation of the marketing knowledge bases. In the third stage, the structure and parameters of the Bayesian network are learned from the outcomes of the first two stages. This paper aims to contribute to the application of Bayesian networks in ERP software industry, which facilitates the knowledge acquisition and marketing strategy generation for enterprise systems providers.

In the rest of this paper, section 2 reviews the factors affecting ERP implementation, which are the foundation of the knowledge bases for ERP systems. Section 3 introduces the basics of the knowledge bases, Bayesian networks. In section 4, the learning process of the Bayesian network on user's attitudes toward ERP systems are presented. Section 5 demonstrates how ERP vendors can take advantage of the Bayesian network in marketing strategy generation. Finally, section 6 gives the concluding remarks.

2. ERP Systems

ERP systems are integrated transaction processing systems that automate core corporate activities such as manufacturing, finance, sales, purchasing, human resources, and so on. Many companies have implemented ERP systems to improve information response time, increase interaction across the enterprise, improve order management cycle, decrease financial close cycle, improve on-time delivery, reduce direct operating costs, and so on. In implementing ERP software, most organizations consider alternative design options and each of these options has its own advantages and disadvantages. Generally speaking, there are four design alternatives to implement ERP systems, vanilla ERP implementation, partial ERP implementation, in-house development, and status quo [1].

In the past decades, many organizations have initiated ERP systems using SAP, Peoplesoft, Oracle, etc. The ERP market is one of the fastest growing markets in the software industry. In APICS' (American Production and Inventory Control Society) research, 34.5% of companies with revenue over \$1 billion who were APICS members planned to purchase or upgrade ERP systems [2]. AMR research predicts that the sales of ERP software will reach \$180 billion by 2002 [3]. According to Bingi et al's study [4], the ERP market may reach \$1 trillion by 2010. Therefore, how to capture the customers' demands and profit from the high-potential market becomes an imperative for ERP systems vendors.

From users' standpoint, many factors may influence the decision on ERP systems adoption, including ERP software system functionality [5-9], information quality [4,5,10], experiences of ERP or related systems [11], costs [4,12-15], expected benefits [1,16-19], pressure from the environments [8,20-24], and so on. The users' attitudes regarding the factors play a crucial role to the decision on ERP systems implementation. ERP systems vendors must design the marketing strategies in harmony with the prospective users' requirements. This study proposes a novel approach, Bayesian networks, in developing knowledge bases of users' attitudes toward ERP systems. Using Bayesian networks, these factors and their interrelationship will be modeled compactly in graphical as well as numerical levels.

3. Bayesian Networks

Bayesian networks [25-28] are directed acyclic graphs (DAG) in which the nodes represent the variables, the arcs represent the direct dependencies between the linked variables, and the dependencies are quantified by conditional probabilities. They are widely used knowledge representation and reasoning models under uncertainty [29-32]. Since a knowledge-based system requires both predictive and diagnostic information, two types of reasoning are common in Bayesian networks, *deduction* and *abduction*. *Deduction*, or prediction, is a logical process from a hypothesis to deduce evidence where probabilistic relationships are involved. *Abduction*, or diagnosis, is a logical process that hypothetically explains experimental observations [27].

An example of Bayesian networks is demonstrated in Fig. 1 and Table 1. There are five variables in Fig. 1: X_1, X_2, X_3, X_4, and X_5. X_1 is the root node in the Bayesian network and its state influences the states of X_2 and X_3. The values of X_2 and X_3 together influence the value of X_4. Finally, the state of X_5 is affected by X_3. In addition to the topology that constitutes the graphical level of the model, a set of prior and conditional probability distributions comprise the numerical level of the graphical model. The probability distributions express the strength of dependency in the Bayesian network.

In building a Bayesian network, the knowledge modeler needs to determine the underlying structure and parameters of the graphical model from the given data set, which includes the quantification of the dependency among the variables. When the structure of the Bayesian network is unknown, the knowledge modelers must first identify the network structure. The objective of structure learning is to find the simplest least expressive structure that optimally describes the Bayesian network's joint probability distribution over the data set. Knowledge modelers usually search for the best structure with a search-and-score procedure. Search-and-score algorithms are methods that heuristically search the space of network structures for the Bayesian network that optimally matches the training data. When the structure is known, the knowledge modelers have to estimate the parameters of the Bayesian network with maximum a posteriori (MAP) process. MAP process requires a parameter prior probability distribution and computes a set of relative frequencies. To acquire the relative frequencies, the MAP process counts the occurrence of each possible value of a certain variable, given each configuration of the parents' states [26-28,33].

Several methods have been developed for abductive or diagnostic reasoning from Bayesian networks. Exact methods exploit the independence structure contained in the network to efficiently propagate uncertainty [25-27]. Meanwhile, stochastic simulation methods provide an alternative approach suitable for highly connected networks, in which exact algorithms can be inefficient [26,27]. Later, search-based approximate algorithms, which search for high probability configurations through a space of possible values, have emerged as a new alternative [34]. Two other approaches have been proposed for symbolic inference in Bayesian networks, namely: the symbolic probabilistic inference algorithm (SPI) and symbolic calculations based on slight modifications of standard numerical propagation algorithms [25,26,35].

Next section shows how the Bayesian network is learned for modeling users attitudes' toward ERP systems.

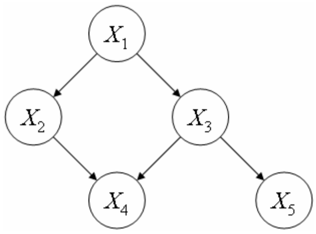

Fig. 1 An example of Bayesian networks

Table 1 Probability distributions in Fig. 1

$P(X_1=1)=0.20$
$P(X_2=1 \mid X_1=1)=0.80$
$P(X_2=1 \mid X_1=0)=0.20$
$P(X_3=1 \mid X_1=1)=0.20$
$P(X_3=1 \mid X_1=0)=0.05$
$P(X_4=1 \mid X_2=1, X_3=1)=0.80$
$P(X_4=1 \mid X_2=0, X_3=1)=0.80$
$P(X_4=1 \mid X_2=1, X_3=0)=0.80$
$P(X_4=1 \mid X_2=0, X_3=0)=0.05$
$P(X_5=1 \mid X_3=1)=0.80$
$P(X_5=1 \mid X_3=0)=0.60$

4. Bayesian Networks

This study conducts a three-stage methodology to learn the Bayesian network of the users' attitudes toward ERP system. In the first stage, this work reviews previous investigations and identifies the factors influencing decision on ERP software implementation. These factors and their relationships will be modeled as a Bayesian network. In the second stage, based on the factors this study designs the questionnaire to investigate the users' attitudes towards ERP systems, which play a critical role in the success of software marketing strategy. The data collected from questionnaire will be further analyzed for estimating the parameters of the Bayesian network. In the third stage, the structure and parameters of the Bayesian network are determined from the outcomes of the preceding stages. Also, the knowledge model will be applied in generating marketing strategy for ERP systems vendors. The research procedure of this work is organized as Fig. 2.

4.1 Factors Influencing ERP Implementation

By voluminous literature review, this work ascertains the factors influencing business decision to ERP software implementation as in Table 2. There are 27 nodes in the Bayesian network: $A_1, \ldots, A_{19}, B_1, \ldots, B_7, C$. In this study, the uppercase represents the variables and the lowercase stands for the value of the variable.

The structure of the Bayesian network is modeled as Fig. 3. Notably the structure does not convey the causal relationships among the nodes. Instead, it illustrates the prior information of the nodes and the mutual dependency among them. The joint probability distribution of the Bayesian network is expressed as (1).

$$
\begin{aligned}
&P(a_1,\ldots,a_{19},b_1,\ldots,b_7,c) \\
&= P(c)\times\prod_{i=1}^{7}P(b_i\mid c)\times\prod_{i=1}^{3}P(a_i\mid b_1)\times\prod_{i=4}^{5}P(a_i\mid b_2)\times\prod_{i=6}^{7}P(a_i\mid b_3) \\
&\quad\times\prod_{i=8}^{10}P(a_i\mid b_4)\times\prod_{i=11}^{12}P(a_i\mid b_5)\times\prod_{i=13}^{17}P(a_i\mid b_6)\times\prod_{i=18}^{19}P(a_i\mid b_7)
\end{aligned}
\tag{1}
$$

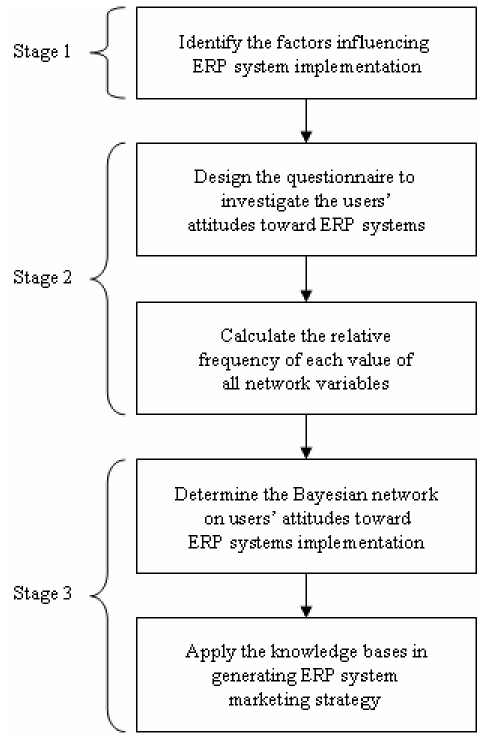

Fig. 2 Procedure for building the Bayesian networks on users' attitudes toward ERP systems

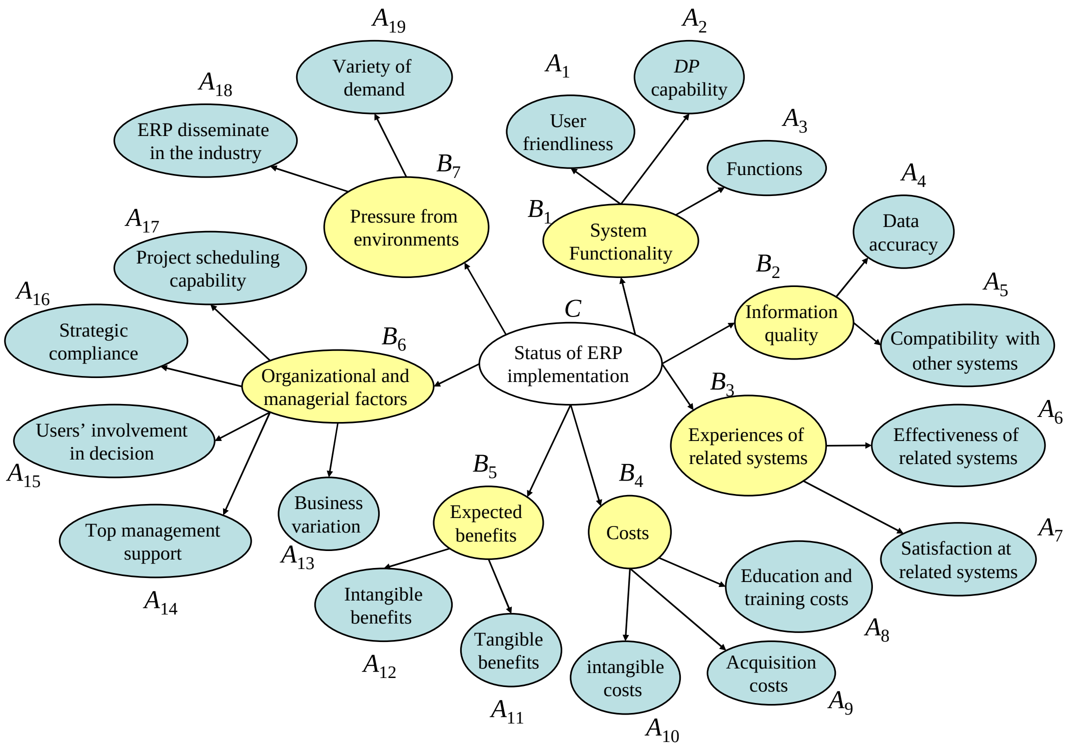

Fig 3 The Bayesian network on users' attitudes toward ERP systems

Each node in the network has three possible states 1, 2, and 3. For variable C (Status of ERP implementation), $C=1$ represents "*ERP systems have been implemented in the company*"; $C=2$ stands for "*ERP adoption is under evaluation or planning*"; $C=3$ represents "*ERP systems is not and will not be implemented in the foreseen future*". As for variables A_i and B_i, the values of 1, 2, and 3 symbolize "*high*", "*median*" and "*low*" for users' weight on each factor's efficacy or manifestation, respectively. In the next stage, each parameter in the graphical model is calculated from the questionnaires data set.

Table 2 The descriptions of the Bayesian network in Fig. 3

Node	Description	Literatures
C	Status of ERP implementation	
B_1	System functionality	[5-9]
A_1	User friendliness	
A_2	Data processing (DP) Capability	
A_3	Functions	
B_2	Information quality	[4,5,10]
A_4	Data accuracy	
A_5	Compatibility with other systems	
B_3	Experience of ERP or related systems	[11]
A_6	Effectiveness of adopting related systems	
A_7	Satisfaction of using related systems	
B_4	Costs	[4,12-15]
A_8	Education and training expenses	
A_9	Acquisition costs	
A_{10}	Other intangible costs	
B_5	Expected benefits	[1,16-19]
A_{11}	Tangible benefits	
A_{12}	Intangible benefits	
B_6	Organizational and managerial factors	[4,36-46]
A_{13}	Level of business variation	
A_{14}	Top management support	
A_{15}	Users' involvement in decision	
A_{16}	Strategic compliance of the systems	
A_{17}	Project scheduling capability	
B_7	Pressure from the environments	[8,20-24]
A_{18}	ERP systems disseminate in the industry	
A_{19}	Variety of market demand	

4.2 Learning the Parameter from Questionnaire Data

To estimate the parameters in the Bayesian network, this study designs a questionnaire to investigate users' attitudes toward ERP systems. These questionnaires are completed by the business employees, including management and non-management levels, who are enrolled in continuing education programs at universities. To guarantee that all respondents have essential understanding of ERP systems, we surveyed the senior at management information systems and business administration programs. Analyzing 300 questionnaires, this study calculates the relative frequency for the probability distribution of each network variable. From Table 3, 48.55% of the respondents witness ERP implementation in their companies ($C=1$); 14.50% are under planning and evaluation ($C=2$); while 36.23% will not adopt ERP systems in the foreseen future ($C=3$).

Table 3. Probability distributions of B_i and C_i nodes in Fig. 3

Category	Probability Distribution		
Current status	$P(C=1)=0.4855$	$P(C=2)=0.1450$	$P(C=3)=0.3623$
Functionality	$P(B_1=1\|C=1)=0.5522$ $P(B_1=2\|C=1)=0.3731$ $P(B_1=3\|C=1)=0.0746$	$P(B_1=1\|C=2)=0.7000$ $P(B_1=2\|C=2)=0.2500$ $P(B_1=3\|C=2)=0.0500$	$P(B_1=1\|C=3)=0.4800$ $P(B_1=2\|C=3)=0.4600$ $P(B_1=3\|C=3)=0.0600$
Information quality	$P(B_2=1\|C=1)=0.5373$ $P(B_2=2\|C=1)=0.4179$ $P(B_2=3\|C=1)=0.0448$	$P(B_2=1\|C=2)=0.7500$ $P(B_2=2\|C=2)=0.2500$ $P(B_2=3\|C=2)=0.0000$	$P(B_2=1\|C=3)=0.5000$ $P(B_2=2\|C=3)=0.4000$ $P(B_2=3\|C=3)=0.1000$
ERP related experience	$P(B_3=1\|C=1)=0.5224$ $P(B_3=2\|C=1)=0.4478$ $P(B_3=3\|C=1)=0.0299$	$P(B_3=1\|C=2)=0.5000$ $P(B_3=2\|C=2)=0.4500$ $P(B_3=3\|C=2)=0.0500$	$P(B_3=1\|C=3)=0.4200$ $P(B_3=2\|C=3)=0.4000$ $P(B_3=3\|C=3)=0.1800$
Costs	$P(B_4=1\|C=1)=0.6716$ $P(B_4=2\|C=1)=0.3134$ $P(B_4=3\|C=1)=0.0149$	$P(B_4=1\|C=2)=0.5500$ $P(B_4=2\|C=2)=0.4000$ $P(B_4=3\|C=2)=0.0500$	$P(B_4=1\|C=3)=0.3800$ $P(B_4=2\|C=3)=0.4800$ $P(B_4=3\|C=3)=0.1400$
Expected benefits	$P(B_5=1\|C=1)=0.4626$ $P(B_5=2\|C=1)=0.5075$ $P(B_5=3\|C=1)=0.0299$	$P(B_5=1\|C=2)=0.6000$ $P(B_5=2\|C=2)=0.3000$ $P(B_5=3\|C=2)=0.1000$	$P(B_5=1\|C=3)=0.4400$ $P(B_5=2\|C=3)=0.4400$ $P(B_5=3\|C=3)=0.1200$
Organizational and managerial factors	$P(B_6=1\|C=1)=0.5970$ $P(B_6=2\|C=1)=0.4030$ $P(B_6=3\|C=1)=0.0000$	$P(B_6=1\|C=2)=0.5500$ $P(B_6=2\|C=2)=0.4500$ $P(B_6=3\|C=2)=0.0000$	$P(B_6=1\|C=3)=0.4400$ $P(B_6=2\|C=3)=0.4400$ $P(B_6=3\|C=3)=0.1200$
Environmental pressure	$P(B_7=1\|C=1)=0.4627$ $P(B_7=2\|C=1)=0.4776$ $P(B_7=3\|C=1)=0.0597$	$P(B_7=1\|C=2)=0.5000$ $P(B_7=2\|C=2)=0.4500$ $P(B_7=3\|C=2)=0.0500$	$P(B_7=1\|C=3)=0.4400$ $P(B_7=2\|C=3)=0.5400$ $P(B_7=3\|C=3)=0.0200$

From the probability distributions, we get specific expectations toward ERP systems by different user profiles. For those whose companies *have adopted ERP systems*, the categories (B_i) drawing most attentions are functionality (B_1), information quality (B_2), costs (B_4), and organizational and managerial factors (B_6). Among the current users, the proportions with high, medium and low concern on costs are 67.16%, 31.34%, and 1.50%, respectively. For those whose companies are in the planning stage, all category factors B_i receive high score from the major proportion. It may be referred to the high expectancy toward a new technology at the early investment stage. Notably, for the respondents *whose companies do not and will not implement ERP systems*, the majority reply with medium to high scores in every category. It provides a valuable marketing implication that potential profitable markets may exist somewhere for ERP systems. A portion of the distributions for the third-level variables A_i are listed in Table 4.

Besides, this study set up an additional variable, D , which measures the subjective decision tendency towards ERP systems if the respondents were decision makers. The variable D provides referential information in predicting the potential users' ultimate attitudes toward ERP systems besides their business profiles. The information of D is listed as follow.

$$P(D=1|C=1)=0.6418\,,\quad P(D=2|C=1)=0.3284\,,\quad P(D=3|C=1)=0.0298$$
$$P(D=1|C=2)=0.6000\,,\quad P(D=2|C=2)=0.3000\,,\quad P(D=3|C=3)=0.1000$$
$$P(D=1|C=3)=0.4800\,,\quad P(D=2|C=3)=0.4200\,,\quad P(D=3|C=3)=0.1000$$

Among the ones whose companies have implemented ERP systems, 64.18% would still implement the systems if they were the decision makers; while only 2.98% are against the proposal. Oppositely, for those whose companies are not using and will not use ERP systems, approximately 50% would approve the implementation and only 10% would disapprove the implementation.

Table 4. Probability distributions of A_i nodes in Fig. 3

Category	Probability Distribution		
Ease of use	$P(A_1=1\|B_1=1)=0.6533$ $P(A_1=2\|B_1=1)=0.2667$ $P(A_1=3\|B_1=1)=0.0800$	$P(A_1=1\|B_1=2)=0.5094$ $P(A_1=2\|B_1=2)=0.4340$ $P(A_1=3\|B_1=2)=0.0566$	$P(A_1=1\|B_1=3)=0.2222$ $P(A_1=2\|B_1=3)=0.3333$ $P(A_1=3\|B_1=3)=0.4444$
Data processing capability	$P(A_2=1\|B_1=1)=0.7866$ $P(A_2=2\|B_1=1)=0.2133$ $P(A_2=3\|B_1=1)=0.0000$	$P(A_2=1\|B_1=2)=0.6226$ $P(A_2=2\|B_1=2)=0.3585$ $P(A_2=3\|B_1=2)=0.0189$	$P(A_2=1\|B_1=3)=0.3333$ $P(A_2=2\|B_1=3)=0.4444$ $P(A_2=3\|B_1=3)=0.2222$
ERP functions	$P(A_3=1\|B_1=1)=0.6933$ $P(A_3=2\|B_1=1)=0.2933$ $P(A_3=3\|B_1=1)=0.0133$	$P(A_3=1\|B_1=2)=0.3208$ $P(A_3=2\|B_1=2)=0.6415$ $P(A_3=3\|B_1=2)=0.0377$	$P(A_3=1\|B_1=3)=0.1111$ $P(A_3=2\|B_1=3)=0.3333$ $P(A_3=3\|B_1=3)=0.5555$
Tangible benefits	$P(A_{11}=1\|B_5=1)=0.6154$ $P(A_{11}=2\|B_5=1)=0.3692$ $P(A_{11}=3\|B_5=1)=0.0154$	$P(A_{11}=1\|B_5=2)=0.2742$ $P(A_{11}=2\|B_5=2)=0.6129$ $P(A_{11}=3\|B_5=2)=0.1129$	$P(A_{11}=1\|B_5=3)=0.1000$ $P(A_{11}=2\|B_5=3)=0.4000$ $P(A_{11}=3\|B_5=3)=0.5000$
Intangible benefits	$P(A_{12}=1\|B_5=1)=0.5846$ $P(A_{12}=2\|B_5=1)=0.3846$ $P(A_{12}=3\|B_5=1)=0.0308$	$P(A_{12}=1\|B_5=2)=0.2742$ $P(A_{12}=2\|B_5=2)=0.6290$ $P(A_{12}=3\|B_5=2)=0.0968$	$P(A_{12}=1\|B_5=3)=0.1000$ $P(A_{12}=2\|B_5=3)=0.1000$ $P(A_{12}=3\|B_5=3)=0.8000$

4.2 Limitation of this Study

This study constructs the knowledge bases with naive-structured Bayesian networks, which assumes the variables in the same level to be independent. There are two advantages of this simple structure. First, it prevents the decision makers from getting confused in analyzing data or making judgments. Second, the concise structure makes maintenance easier and feasible. Some correlation among the variables may be ignored. However, after checking the probability distributions, the knowledge bases are expressive in describing the dependency. Hence, this study regards the limitation as mild.

5. Queries from the Knowledge Bases

This section demonstrates how strategy planners apply Bayesian network to ERP software marketing. Consider the following scenarios.

Case 1: Consider a potential customer with the following demands and profiles: high system functionality ($B_1=1$), high information quality ($B_2=1$), few experiences of related systems ($B_3=3$), median costs concern ($B_4=2$), high expected benefits ($B_5=1$), median organizational and managerial concerns ($B_6=2$) and low environmental pressure ($B_7=3$).

The above information constitutes the evidence set $E=\{e\}=\{B_1=1, B_2=1, B_3=3, B_4=2, B_5=1, B_6=2, B_7=3\}$. This study computes the belief for this customer to implement ERP systems as follow.

$$P(C=1\,|\,e)=\frac{\sum_{a_1}\ldots\sum_{a_{19}}P(a_1,\ldots,a_{19},C=1,e)}{\sum_{a_1}\ldots\sum_{a_{19}}\sum_{c}P(a_1,\ldots,a_{19},c,e)}=0.1223$$

$$P(C=2\,|\,e)=\frac{\sum_{a_1}\ldots\sum_{a_{19}}P(a_1,\ldots,a_{19},C=2,e)}{\sum_{a_1}\ldots\sum_{a_{19}}\sum_{c}P(a_1,\ldots,a_{19},c,e)}=0.5603$$

$$P(C=3\,|\,e)=\frac{\sum_{a_1}\ldots\sum_{a_{19}}P(a_1,\ldots,a_{19},C=3,e)}{\sum_{a_1}\ldots\sum_{a_{19}}\sum_{c}P(a_1,\ldots,a_{19},c,e)}=0.3174$$

$$P(C=1,2\,|\,e)=0.1223+0.5603=0.6826$$

The results show that this is a potential user profiled with significant probability (0.6826) to implement ERP systems. If we compute the posterior probability that the decision maker will approve deploying ERP systems, the results are computed as follow.

$$P(D=1|e)=\sum_{c}P(D=1|c)P(c|e)=0.5670$$

$$P(D=2|e)=\sum_{c}P(D=2|c)P(c|e)=0.3416$$

$$P(D=3|e)=\sum_{c}P(D=3|c)P(c|e)=0.0914$$

Both results favor investing this sales opportunity. Because the customer has high demands on system functionality ($B_1=1$), information quality ($B_2=1$) and expected benefits ($B_5=1$), the marketing strategy should be stressed on the relevant aspects in accordance with the customer's preference.

Case 2: Consider another business with the following requests and characteristics: median ease of use ($A_1=2$), high data processing capability ($A_2=1$), median functions ($A_3=2$), high information quality ($B_2=1$), low experiences of related systems ($B_3=3$), high costs concern ($B_4=1$), high tangible benefits ($A_{11}=1$), median intangible benefits ($A_{12}=2$), median organizational and managerial concerns ($B_6=2$) and high pressure from environments ($B_7=1$).

The above information constitutes the evidence set $E=\{e\}=\{A_1=2,\ A_2=1,\ A_3=2,\ B_2=1,\ B_3=3,\ B_4=1,\ A_{11}=1,\ A_{12}=2,\ B_6=2,\ B_7=1\}$. Similar to case 1, the belief distribution of this customer to implement ERP systems is calculated below.

$$P(B_1=1|e)=0.2263,\ P(B_1=2|e)=0.6376,\ P(B_1=3|e)=0.1361$$
$$P(B_5=1|e)=0.5647,\ P(B_5=2|e)=0.4115,\ P(B_5=3|e)=0.0238$$
$$P(C=1|e)=0.1590,\ P(C=2|e)=0.3141,\ P(C=3|e)=0.5269$$

The results show the customer as a potential user profiled with fair probability (< 0.5) to implement ERP systems. The ERP vendor may consider withdrawing from this opportunity. However, if we look at the probability that the decision maker favors ERP solutions as below, this sales opportunity is worth investment.

$$P(D=1|e)=\sum_{c}P(D=1|c)P(c|e)=0.5434$$

$$P(D=2|e)=\sum_{c}P(D=2|c)P(c|e)=0.3677$$

$$P(D=3|e)=\sum_{c}P(D=3|c)P(c|e)=0.0888$$

Since this customer tends to demand high information quality ($B_2=1$), high expected benefits ($B_5=1$), and faces high pressure from environments ($B_7=1$), the marketing strategy should accentuate the relevant utility to reinforce the customer's motivation in adopting ERP systems.

6. Conclusion

This study proposes a novel approach, Bayesian networks, in developing knowledge bases of users' attitudes toward ERP systems. Using the Bayesian network, the factors and their interrelationship will be modeled compactly in graphical as well as numerical levels. The ERP systems vendors can employ the knowledge bases in motivating potential users and predicting the sales opportunity. This paper aims to contribute toward the knowledge acquisition and marketing strategy design for the enterprise systems industry.

Acknowledgment

The authors appreciate the comments from the anonymous referees to enhance the readability of this article. This study is supported by Taiwan Merit Scholarships, No. TMS-094-2-B-009 (Han-Ying Kao) and Taiwan Merit Scholarships, University-based Program Regulation, No. 94B514 (Chia-Hui Huang).

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