2010

IT and the Environment: An Application in Supply Chain Management

Lee Hu
Peking University, lhu@pku.edu.cn

Daniel Zeng
Peking University, dzeng@pku.edu.cn

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Lee Hu, Peking University, Beijing, China, lhu@pku.edu.cn

Daniel Zeng, Peking University, Beijing, China, dzeng@pku.edu.cn

Abstract

The development of new and improved Information Technology (IT) methods for Supply Chain Management is important. Existing methods suffer from several shortcomings, especially the ability to deal with a mixture of quantitative and qualitative data. This study aims to apply decision support techniques to the area of Supply Chain Management in order to address some of the shortcomings.

The methodology follows structuring and modeling. A three-step decision structuring framework is used to develop a model, based on Bayesian networks, to support Supply Chain Management scenarios. The result is a Bayesian network that incorporates the knowledge of experts into a decision support model. It is shown that the model is essential as it contains all the vital elements of the problem from a managerial viewpoint.

The described model can be used to perform what-if analysis in various ways, thereby supporting the management of risk in different scenarios. The contribution of this research is not limited to the model, but the study also provides insights into how decision support, and especially Bayesian networks, can enhance IT methods.

Keywords: Information Technology, Supply Chain Management, Bayesian networks.

1 INTRODUCTION

Many business executives are often faced with choices such as “Should the business expand or consolidate?”, “Should excess cash be used for capital expansion or paid out as dividends?”, “What new product should be developed from the choices available?” Such choices are not easy to make and managers needing to make such choices could benefit from decision support (Chen and Fang, 2009).

Furthermore, the current recession poses new challenges to IT executives. The relatively consistent top managerial concerns in previous years are making a shift toward concerns which are tightly related to the unique characteristics of this recession. In previous downturns, business executives turned to their IT functions and asked them to simply cut their budget. In this recession, which is considered worse than previous ones, business executives are rethinking the role of IT and they are now asking IT to work with the business to reduce company costs and to improve the productivity of the rest of the business. While this recession presents new challenges and opportunities for IT executives in 2009, the prognosis for 2010 is to proceed with conservative caution (Luftman and Ben-Zvi, 2010).

In both the manufacturing and services sector new products are constantly being developed. A company normally choose not to risk all on the development of only one product but develops a portfolio of products. Such a portfolio normally consists out of products chosen from a multitude of possibilities (Ben-Zvi and Grosfeld-Nir, 2010; Ding and Chen, 2009; Porn-Apirat, 2007).

Various such portfolio management methods exist. These methods can be grouped together in the following categories (Chen et al., 2006): Financial models and financial indices, Probabilistic Financial models, Options pricing theory, Strategic Approaches, Scoring models and checklists, Analytical hierarchy approaches, Behavioral approaches, and Mapping approaches.

Current methods of technology management in general suffer from a number of specific shortcomings. These shortcomings includes: Ignores probabilities and risk (Cooper, 2010), Depends on extensive financial and other quantitative data, Considers only financial criteria, Force choices need to be made, A small number of factors are taken into account, The interrelationships between factors are not addressed, More than one tool is necessary to address the issues (Cooper and Edgett, 2010), and Inability to take into account qualitative implications (Irani et al., 2002).

Liao (2005) performed a literature study on technology management methodologies and applications. In the suggestions it is stated that the qualitative and quantitative methods are different in both methodology and problem domain and that the integration of qualitative and quantitative methods may be an important direction for future work on TM methods.

IT can be improved by approaches that support the creation of shared mental models (Carbonara and Scozzi, 2006). The aforementioned methods use both qualitative and quantitative data but separately therefore not creating a shared mental model. It could therefore be argued that a management model that will enable the integration of both qualitative and quantitative methods over the different phases of the product development supports the development of a shared mental model and this will enhance the state of technology management. The purpose of this research is to move in a direction of decision methods incorporating both qualitative and quantitative approaches.

The research problem therefore includes the finding of a management or decision support method that will be able to simultaneously deal with both qualitative and quantitative data and be able to provide inputs at the different stages in the product development cycle. The model must also integrate the various aspects into a single visual model that can be shared and discussed among different experts and decision makers. This focus underscores the importance of Technology and its ability to support different functions (Myburgh and Smith, B., 2009).

A Bayesian Network (BN) creates a visual model that indicates the causal relationships between various aspects in the model. A BN can also deal with uncertainty and missing data and allow the user to experiment with possible outcomes (What-if? analyses). It is believed that a BN based model for new product development will address the issues discussed above. This research will therefore focus on the development of a Bayesian network based model to support new product development decisions.

1.1 Previous Research

While a variety of existing methods proposed for analyzing supply chain management still have the capability of studying static chains systematically, most of them are limited to dynamic supply chains when underlying information in the networks is ignored, such as time. Consequently, we turn to taking full use of those underlying information models because the developments in methods in recent years have not been able to catch up with the developments in the field. The dynamic supply chain management model described in the literature generalizes a dynamic model into which incorporates several components of supply chain management over time, in order to predict future transactions and interactions.

Carbonell-Foulquie et al. (2004) did a study on the criteria and weightings used in the development of new highly innovative products. A highly innovative product was defined as a product that offered new or unique benefits or solutions for market needs and involved great design and production challenges. Questionnaires were presented to companies involved in highly innovative IT. In the questionnaires a four stage IT cycle and sixteen criteria, compiled from literature, were presented. The four stage IT cycle consisted of the stages: Development of new product concept and test, Simulation of product design and analysis of production process, Product and process development and test, and Production and market launch. At the end of each of these stages was a go/no-go decision gate. In the analysis of the results Carbonell-Foulquie et al. (2004) eliminated three criteria due to the low level of indicated significance on making go/no-go decisions. These were: leverage of marketing skills, product patentability, and payback time. The remaining criteria were: availability of resources, opportunity window, project alignment with firm's strategy, marketing synergies, technical/R&D synergies, project total cost for a given cycle time, product quality, market acceptance, customer satisfaction, sales volume, market growth, margin rate, and internal rate of return.

Carbonell-Foulquie et al. (2004) performed a factor analysis on the criteria and found a five-factor solution. Factor analysis and the varimax rotation implemented by Carbonell- Foulquie et al. (2004) is explained in (Larpse, 2006). The factors identified were named: Technical Feasibility, Strategic Fit, Customer Acceptance, Financial Performance and Market Opportunity.

The criteria that contribute to each factor are stated below. Technical Feasibility consisted of: estimation of project total cost, availability of resources, leverage of firm's R&D, engineering, and manufacturing skills. Strategic fit included criteria: Alignment of project with firm's strategy and window of opportunity. Customer acceptance included three criteria namely: Market Acceptance, customer satisfaction and product quality. Financial performance is influenced by Margin Rate, Internal rate of return and sales volume. The last factor, Market Opportunity, included criteria Sales growth and Market share.

Further analyses by Carbonell-Foulquie et al. (2004) identified the relative importance of the factors in the various IT stages. The importance factors are not situation specific as the survey respondents belonged to different industries (43% mechanical machinery and equipment, 22.6% electrical machinery and equipment, 14.5% electronics and computers, 19.4% motor vehicles and other transports, 0.5% not stated (Carbonell-Foulquie et al., 2004). This also indicated the contributions made by the various criteria on the factors.

In addition, The exponential growth of information and technology in recent years necessitates a more thorough understanding of stored data and information. Information and data are being accumulated in pace never seen before and traditional methods of handling those huge amounts are just not sufficient. This is particularly true in the healthcare industry. A search for a resolution yielded many potential solutions. One popular approach that is frequently being used in industry and that was proven quite efficient in analyzing data is Data Mining (Porter and Green, 2009). Today, data mining tolls are widely used to understand marketing patterns, customer behavior, examine patients' data, and detect fraud (Duchamp and Green, 2009; Fang, 2009).

1.2 Decision Support Models

It is argued that technology management decisions are hard and therefore requires decision making support/science. Clemen and Reilly (2001) indicate four reasons why decisions are hard: Due to the complexity of the problem, because of inherent uncertainty in the situation, because the decision maker may be interested in working towards multiple objectives but progress in one direction impede progress in others, and because different perspectives lead to different conclusions (Chen and Lin, 2009b).

New product development is characterized by a tremendous degree of complexity and uncertainty and involves choosing between different products competing for the same funding. Given this it can therefore be said that new product development decision are hard and therefore in need of decision support (Chen and Lin, 2009a).

Decision analysis provides structure and guidance for systematic thinking in difficult situations; it does not provide an alternative that must be blindly accepted (Clemen and Reilly, 2001). Subjective judgment will always form part of any difficult decision (Chen and Lin, 2009c).

Clemen and Reilly (2001) states that personal judgments are important ingredients for making good decisions. Any model supporting IT decision making must therefore allow for subjective inputs. Clemen and Reilly (2001) indicate that modeling is critical in decision analysis. In this research a Bayesian Network modeling approach is used. This approach provides a graphical and mathematical representation of the situation.

From a decision analysis perspective such models have a key advantage in that they allow for analysis which can indicate a "preferred" alternative. A Bayesian network is a probabilistic model and according to Irani et al. (2002) such a network is an effective modeling framework for the following reasons: it captures the structural aspects of the decision, it serves as a framework for and efficient quantitative analysis, allows sufficient representation and exploitation of conditional independence in a decision model, and has proven to be an effective tool for communicating decision models among decision analysts and decision makers, and between the analyst and the computer. This interplay between IT and decision support is mediated by data mining (Woo and Hu, 2009).

Business value of information technology in general, and decision support systems in particular are a major concern to any company today. The adoption of information technology with its variety of components, such as information systems, expert systems and decision support within the health care sector is extremely important as data is being accumulated in a faster pace than ever. Implementing information technology in healthcare settings has been the focus of many information system researchers in the last few years (Chen and Lin, 2009c).

2 THE MODEL

Embedded in the model is hidden an important aspect of modeling, and using models to enhance decision making. The model is built for the purpose of assisting a better understanding of a situation. Models are, and will always be, approximate representations of reality. Pidd (1996) states that it is not necessary for a model to be exact to be of use. Pidd (1996) goes further to state that it is precisely because models are approximations of the reality that makes them useful.

A Bayesian network (BN) is used to model a domain containing uncertainty in some manner. This uncertainty can be due to imperfect understanding of the domain, incomplete knowledge of the state of the domain at the time a given task is to be performed, randomness in the mechanisms governing the behavior of the domain, or a combination of these.

Structuring decisions require three fundamental steps. The first is to identify the values and objectives. In this study the values (what is important to the decision maker) is the potential return on investment indicated at the different stage gates in the IT process. The objectives (important aspects taken together that form the values) are the different aspects that influence the investment returns. Carbonell-Foulquie et al. (2004) identified thirteen relevant criteria and provide quantitative information regarding the use of the criteria. It was therefore chosen to use these criteria as the influencing aspects.

The second step is structuring the elements of the decision situation into a logical framework. A graphical model is always useful and normally easier to understand than a complex equation. It was therefore chosen to use a technique that includes graphical modeling. Bayesian networks provide a means of building a logical framework using a simple graphical causal model.

A Bayesian network is built in two stages. The first stage is the graphical model indicating the various nodes and the causal influences between the nodes. The second stage is the population of the probability tables, the quantitative aspect of the model. This second stage form part of the third step of structuring decisions.

A first level conceptual decision model for new product development is shown. This conceptual model has the following characteristics: First, it makes provision for different IT development stage gates and models the potential success return for each of the stages in the IT cycle. Second, the model groups certain criteria into different factors that influence the IT Returns. All the criteria can therefore influence each of the IT stages through the different factors.

Studies in literature usually explore optimization problems that maximize profits or minimize costs in relation to decision support. This has been the dominant research in many environments for decades (Po and Deng, 2010). Although the optimization goal is noble in itself, we discovered that it may not be the case in reality, when one implements the model. When considering production processes, manufacturers may become prude and maximize their own utility function, which may not coincide with minimizing costs. That utility function may include several other important factors such as costs, revenues, market share, and also risk.

2.1 Concepts

As discussed in section earlier Carbonell-Foulquie et al. (2004) used a four stage IT process. The nodes indicating the potential return at the four stage gates are named: New Product Concept Return, New Product Design Return, Production Startup Return, and Keep On Market Return. The thirteen relevant criteria, grouped into five factors identified by Carbonell-Foulquie et al. (2004), each forms a node in the network. Arcs from specific criteria to the relevant factors indicate the criteria influencing a specific factor (e.g. Sales Growth and Market Share influence Market Opportunity). Arcs from each factor to each stage gate (Return node) indicate that each factor influence each stage gate. One assumption made during the development of the causal relationships is that the criteria that influence a factor do not change between IT stages. When this information is used the model shown is the result. For reference purposes the naming is kept the same as that used by Carbonell-Foulquie et al. (2004). This completes the first phase of the model realization and the second step in the structuring of decisions.

The third step in structuring decisions is the refinement and precise definition of all the elements of the decision model. This relates to the second step of building a BN. The second step of building the BN is to associate probabilities with the causal relationships defined in the first phase. Where the results of Carbonell-Foulquie et al. (2004) was used directly to implement phase one, the results require interpretation for the second step of implementation.

2.2 States and Actions

The first action in the quantitative modeling phase is to define appropriate states for each of the nodes. States can be text, numerical, or numeric intervals. Due to the large number of possible states in the model (explained later) it was decided to use numerical intervals. This made the use of expressions to define the states possible as manually defining all possible states would not be feasible. Starting with the different criteria it was chosen, in order to keep the initial model simple, for all criteria to have three states 1, 2 and 3. These states can be interpreted appropriately from worst to best for each of the criteria.

The states of the factors are determined by the criteria that influences each state. It was chosen to normalize any contributing criteria so that the factor values will always be between 0 and 1. This eased the understanding of the outputs and the development of the expressions determining the probabilities of the IT Return nodes. Again it was chosen to have three states for each factor. The factor states indicate intervals for the result of the expression that determine the factor value. Again these states can be interpreted appropriately from worst to best for each of the factors.

The states of the IT Return nodes are determined by the possible states for the factors and the weightings of the relationships. It was found that a granularity of only three states for the IT Return did not provide sufficient resolution to aid understanding of the results. It was therefore chosen to implement four states for the IT Return nodes.

A relevant question in decision modeling is whether the developed model is the appropriate one. Clemen et al. (2001) discusses the concept of a requisite model, first introduced by Phillips (1982). A model is requisite when the decision maker's thoughts about the problem, beliefs regarding uncertainty and preferences are fully developed. Stated differently; a requisite decision model is one that contains the essential elements of the problem from which a decision maker can take action.

The question of being requisite is applied to the developed model. The proposed model includes the thoughts and preferences of a number of successful IT managers in terms of the criteria and the relative importance of the criteria at the various gates in the IT process through the survey process performed by Carbonell-Foulquie et al. (2004). The model allows a decision maker to include beliefs regarding uncertainty in the model by changing the probabilities of the criteria. The model also addresses certain specific decision points (stage gates) in the IT process and therefore provides action assistance at these points. Based on the above it is argued that the proposed model is a requisite decision model.

3 RESULTS

To discuss the results of the model outputs, information (also called evidence when dealing with Bayesian Networks) is entered into the model. The changes such evidence effect is then observed.

The realized model with no evidence entered shows a high probability for medium returns in all three stages. This is based on equal probabilities for the sixteen input criteria.

The benefit of the Bayesian network is that evidence entry is not limited to the input nodes, in this instance the criteria nodes. Evidence can be entered at any of the nodes and will propagate through the network.

As previously indicated the model is based on the analysis of Carbonell-Foulquíe et al. (2004). If the model implementation is correct the same deductions must be possible from the model as was made from the paper results.

The paper results indicate that Strategic Fit is more important in the early stages than later on in the development cycle. For the first IT Stage (New Product Concept) the model results show a 83.63% required probability for high Strategic Fit. This required probability diminishes for the later IT stages and is only 48.64% for the last stage (Keep on Market). Clearly the model results are in line with the paper results indicating higher Strategic fit earlier in the IT cycle.

The paper results also indicate that Technical Feasibility is more important over the Concept and Design phases (Required probability of High Technical Feasibility of 84% and 88.84% respectively vs. 80.82% and 47.10%). The model is in agreement with this but also indicate that technical feasibility also has an important part to play during production start up.

Customer Acceptance is indicated in the paper results as important throughout the process but especially after product launch. The model shows a high probability requirement for Customer Acceptance for all stages (85.80%, 91.52%, 90.62% and 99%) with the highest required level for Customer Acceptance (99%) at the Keep On Market stage, that is after the product has launched. This is in line with the paper results.

The model indicates that Financial Performance importance is fairly constant over the IT stages. A slight increase towards the later stages is in line with the paper results.

The model was built based on the results from Carbonell-Foulquíe et al. (2004). Seeing that the model results, given certain evidence, reflects the same interpretation as the results from the paper study indicate that the model was correctly implemented. It can therefore be stated that the model provides valid results for the importance of criteria influencing new product development over different stages.

Another useful way of using the model would be to enter achieved states for the various criteria or leave the criteria at the a priori (formed or conceived beforehand) distributions if no evidence is available and then see the influence on the IT Return for the various stages. Each of these sets can be seen as a scenario.

This scenario could be described as: A new product of medium cost is to be developed. The product is within the company's niche area and would therefore leverage the company resources very well. It is unknown whether the resource would be available and no evidence of this is entered. The product is very well aligned with the company strategy and the window of opportunity is good but not extremely so. It is not sure how good the market acceptance or customer satisfaction would be. It is clear that a product of high quality can be developed. Calculation shows that the margin rate and IRR would be medium good. The sales volume can not be predicted at this stage. Both sales growth and market share is predicted to be medium.

The results can be interpreted as: The technical feasibility of the project is high (63% likely) to medium-high (33% likely). The project strategic fit is perfect. Whether the customer acceptance would be high (55% likely) or medium-high (44% likely) is unsure. The project's financial performance and market opportunity are predicted to be medium.

All this translates into a high probability (almost 80% in all stages) of achieving a medium-high return in all stages, zero probability of achieving only a low return at any of the stage gates, and small probabilities to reach a medium-low (1.68% to 12.26%) or high return (6% to 17%). The power of the Bayesian network lies in the ability to perform what-if analysis.

This new what-if evidence is entered and then propagated through the network and provides new information on both the influence on the IT Returns as well as on what is required on the criteria side to achieve a high customer acceptance.

The results can be interpreted as follows: For all stages the probability of achieving a medium-low return becomes zero. This is not a big influence as the original probabilities were already very low. Increasing customer acceptance to high will almost double the probability of indicating a high return at the design stage (from 17% to 31%). The same applies to the Production Startup stage (probability for high return changes from 13% to 24%). Also of significance is that the 12% probability of indicating only a medium-low return for the Keep on Market stage disappears.

From the results the company could decide that it would be worthwhile to pursue the achievement of a high customer acceptance level. The question would now be what needs to be done in order to achieve this. Changes is only required in the Market Acceptance and Customer Satisfaction criteria. The required changes are actually not that dramatic. For market acceptance only a small change is required (increasing the medium and high probabilities by 7% and decreasing the low probability by 10%). For Customer Satisfaction the low probability need to be eliminated in the process increasing medium to 40% and high to 60%.

Without the model the company could have argued that ensuring the necessary resources is available or by ensuring high sales volume would be a better approach to ensure a better return. An increase in sales volume actually has no influence as the probability for a medium financial performance remains 100% and therefore no changes in the indicated IT Returns are evident.

The actual changes in IT return with high availability of resources are shown. The changes in IT Return for this scenario is actually less than what was achieved when increasing Customer Acceptance. The model therefore allows what-if analysis and easy interpretations of the results.

4 CONCLUSIONS

The objective of this study was to test the following:

Applying decision support techniques (specifically Bayesian Networks) to the area of New Product Development will address some of the primary shortcomings in currently applied approaches and progress towards an integrative approach.

The research approach was one of decision structuring and modeling. The result was a Bayesian Network based model to support new product development decisions over several development stages (stage gates).

This research established a Bayesian Network model based on case study results of successful highly innovative product developments. How Bayesian Networks can be implemented in order to develop a decision support system in the management of new product development domain was shown through the process of realizing, implementing and analyzing the BN. From this readers may identify others areas of management where BNs may successfully be implemented.

This study contributes a Bayesian Network model based approach to the management area of new product development. This model addresses various aspects of new product development over multiple stages. The model is implemented in software and can therefore be used in a real world setting as well as for theoretical research. The model can deal with quantitative and qualitative input and missing data. The model therefore exhibit the required characteristics indicated earlier.

This study contributes to the field of management in general by showing how a decision support technique such as Bayesian Networks can be implemented to address a real world problem. This study directly contributes to the field of new product development by taking paper results that would be difficult to implement in a real world situation and creating a useable, customizable and extendable decision support model.

This study also opens opportunities for further research. Further models can be developed to support the input criteria and can be added to the model. Further validation of the model can be performed, also including comparisons with methods not based on Bayesian Networks. The implementation of a graphical user interface hiding the complexities of the Bayesian network can be researched.

Expanding the states in the model and research regarding various sensitivities in the model can also be conducted. Case studies in various environments can be conducted to specialize the model for specific environments.

As companies today face the worst financial crisis in decades. CEOs and other company executives are expected to prove their leadership role, while they continue to struggle with cost reductions, business agility, and re-engineering. We note that IT executives are required to make an effort and help the organization at these times. IT and the business working closely together in these troubled times and that would probably be the key to bring companies and organizations out of the recession to prosperity and growth in future years. We emphasize that IT is not the only function that makes an effort and contributes to the company, but in this recession, IT seems to play a major role.

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