AN INTEGRATED DECISION SUPPORT SYSTEM FOR NEW PRODUCT DEVELOPMENT WITH CUSTOMER SATISFACTION

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An Integrated Decision Support System for New Product Development with Customer Satisfaction

By

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CERTIFICATE OF ORIGINALITY

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ABSTRACT

New product development (NPD) is vital to business success. Companies launch profitable and attractive products to satisfy customers as well as gain profits and market share. New products are a crucial driver of customer satisfaction, and that customer satisfaction plays a key role in business growth. It is clear that NPD and customer satisfaction are associated. In the NPD process, decision making at the front end is particularly important as it helps companies concentrate on developing competitive and customer-focused products instead of investing in worthless ones. Such decision making is complex and the existing decision support systems (DSSs) are nevertheless ineffective. A new and innovative approach of DSS is therefore proposed to aid companies in making sophisticated and reliable decisions on NPD.

A framework of an integrated decision support system (iDSS), which is novel and significant, is designed to support NPD. A mixed methodology is adopted and several decision-making techniques are employed, including the scorecard technique, Markov analysis, the fuzzy analytic hierarchy process, and system dynamics. The iDSS contains three modules, namely Module I: an idea screening decision model, Module II: a customer perception model, and Module III: a dynamic decision model. Each module serves specific purposes. Module I is designed to predict the success probability of new product ideas and provide the optimal intervals for making the exact go or kill decisions on all ideas. Module II aims to weigh and prioritize product characteristics, which are corresponding to customer requirements. Ideas selected through Module I would be further developed and evaluated in detail in Module III for approval while the results of Module II would be input into Module III. Module

III serves to provide a financial estimate, which is the net customer lifetime value (NCLV), taking into account the time value of money and on-going customer relationships. Projects with higher NCLVs satisfy customers and bring profits to the company in the long term, thus worth further investment.

Three case studies were conducted to validate the iDSS and to highlight its feasibility. They are based on a world-class company in the power tool industry and supported by extensive data collection, a customer survey, and interviews of this company. The company accounts for over 30 percent of global market share in 2010. It has been listed on the Stock Exchange of Hong Kong since 1990. The case studies are related to the specific needs of the company and are a part of the Teaching Company Scheme. From the case studies, it is found that the company should make go decisions on new product ideas whose success probability lies in the interval [0.53, 1]. These selected ideas will be further investigated and regarded as NPD projects. The company should emphasize the durability (the durability of surviving from drops), efficiency (to complete applications quickly and easily), and robustness (the ability to endure tough applications) of power tools as these are the top three important factors prompting customers to initiate a purchase. Before further development and production, detailed evaluation of the NPD projects is required. It is found that the NCLV calculation is useful to determine the value of NPD projects in the long term. Projects with higher NCLVs are more profitable, and thus worth further investment and launch. The iDSS is proven to be effective and convincing through the case studies. It aids companies in selecting and developing new products that could satisfy customers to build long-term customer relationships and generate greater profits; this improves the quality of the NPD decision making.

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Book Chapter

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

AHP	Analytic hierarchy process
CLV	Customer lifetime value
CN	Customer needs
CRM	Customer relationship management
DSS	Decision support system
FAHP	Fuzzy analytic hierarchy process
HMM	Hidden Markov model
iDSS	Integrated decision support system
LDS	Logistics and distribution strength
MA	Marketing approach
MANU	Manufacturability
ME	Marketing effectiveness
MS	Market strength
NCLV	Net customer lifetime value
NPD	New product development
NPIS	New product idea screening
NPV	Net present value
OCS	Overall customer satisfaction
OPA	Overall product attractiveness
RA	Remarketing approach
RB	Risk buy
RE	Remarketing effectiveness

TC	Technical competency
TCS	Teaching Company Scheme
WOM	Word of mouth

CHAPTER 1 INTRODUCTION

1.1 Research Background

As the HKSAR Policy Address (Tsang, 2009) stated that the government supports the promotion of independent innovations of business, development of high value-added products, and enhancement of the technological level of industries, in order to consolidate Hong Kong's status as an international centre. This draws our attention that innovative new product development (NPD) plays an important role in improving global competitiveness of all business sectors.

In this research, "successful NPD" refers to a product that can be well developed in the NPD process from idea generation to product launch and can help companies gain return on investment. Successful NPD that delivers true customer value is a competitive weapon that helps companies defeat rivals and dominate dynamic markets. As stated by Ravald and Gronroos (1996, p.19), "the ability to provide superior value to customers is a prerequisite when trying to establish and maintain long-term customer relationships." Obviously, NPD and customer relationships are closely associated. If relationships are successfully established and customer values created and delivered to customers, NPD would become a success. Indeed, successful NPD facilitates companies to penetrate markets and to achieve commercial success through not only building and maintaining customer relationships but also satisfying the needs of both potential and current customers. Indeed, customer satisfaction is fundamental in the NPD practices. It has been empirically established that customer satisfaction leads to customer loyalty and, in the long term, to profitability (Heskett *et al.*, 1994; Murphy *et al.*, 2005). By delivering value through new products, companies satisfy customers, and then build and retain long-term relationships with customers, which consequently generate value, such as profits and market share. The value creation and capturing process through NPD is emphasized. The process shows that NPD, customer satisfaction, and customer relationships are associated. Hence, many companies actively engage in developing new and attractive products so as to maximize and capture value, thus surviving in the fierce competition of the business world.

Today, ever-changing customer demands, technological advancement, and intense global competition challenge companies to succeed in satisfying dynamic market requirements through NPD. To survive in the current business environment, companies usually focus on several areas to improve their NPD, such as identifying customer requirements for continuous NPD (Melissa, 2005; Liu *et al.*, 2008), improving product quality (Kwong and Bai, 2005; Swink *et al.*, 2006), and accelerating the process of commercialization (Melissa, 2005; Swink *et al.*, 2006; Xu *et al.*, 2007a). Numerous decision support systems (DSSs) are available in the literature that aid product classification (Mohanty and Bhasker, 2005), single product design (Balakrishnan and Jacob, 1995; Mohan *et al.*, 2007; Xu *et al.*, 2007a), product line design (Zha *et al.*, 2004; Alexouda, 2005; Kumar *et al.*, 2007), and market-based product development (Moskowitz and Kim, 1997; Herrmann *et al.*, 2000; Harding *et al.*, 2001; Chen *et al.*, 2002; Khoo *et al.*, 2002; Alexouda, 2005). This literature shows that customer-oriented and market-driven NPD is particularly emphasized and has been a popular literature topic in recent years.

Despite growing research efforts and investment made to the issue, the success rate of NPD has not been improved. The practices of NPD still involve a high risk of failure and are costly. Stevens and Burley (1997) cited that only one new product can be launched successfully to achieve commercial success among 3,000 raw new product ideas. Berggren and Nacher (2001) estimated that the failure rate of new products is around 95%. Bianchi (2004) further indicated that over 50% of new products launched have failed within two years and caused a total loss of $100 billion per year. This is mainly attributed to ineffective decision making in NPD.

Decisions on NPD are complex but crucial. In this research, “new product ideas” are defined as new product concepts that are undeveloped and unable to be regarded as new products, while “NPD projects” refer to the projects wherein new product ideas are well defined and approved to be further developed in the NPD process. NPD, from idea creation to product introduction, involves several phases and decision gates. The NPD practice is a multi-disciplinary activity which requires knowledge integration and application. Inter-departmental communication among designers, engineers, and marketing personnel is needed. It is challenging to reach a consensus among the various parties involved in NPD, who have different responsibilities and concerns. In most circumstances, once managers decide to further develop new product ideas, they are unlikely to terminate the ongoing NPD projects (Balachandra, 1984; Schmidt and Calantone, 1998). Instead, they prefer to take risks and invest more, trying to complete the projects. This then results in economic loss and loss of market share if the NPD projects unfortunately fail to be manufactured or launched. In addition, costs often rise dramatically as NPD projects move toward commercialization. NPD is always a challenging task but it plays an important role in business growth and profitability. To achieve a competitive edge in a market, sensible decisions must be made about various aspects of NPD, such as product attributes, customer acquisition and retention, as well as promotion and marketing strategies. These decisions are inter-linked and will ultimately affect the outcome of NPD.

Decision aids such as a DSS are thus of benefit in solving such decision problems. A DSS can provide managers with useful information to understand the managerial aspects of decision problems and to make appropriate decisions. As mentioned earlier, NPD and customers are connected while customer satisfaction is fundamental in the NPD practices. This research, which focuses on proposing an integrated decision support system (iDSS) for NPD with a consideration of customer satisfaction, is then initiated.

1.2 Problem Statements

Five problems, identified in Problem Statements A-E, are discussed as follows:

A. Unable to make appropriate screening (either a go or kill) decisions for all new product ideas

New product idea screening (NPIS) at the front end of the NPD process plays a crucial role in the NPD practices. In comparison to other NPD activities, the highest correlation is shown between the initial NPIS and new product performance (Cooper and Kleinschmidi, 1986). Performing an initial NPIS to eliminate potentially inferior and worthless new product ideas before development, production, and commercialization can prevent companies from investing unrecoverable money, time, and resources. Therefore, there is a great necessity to eliminate inferior new product ideas as early as possible at the front end of the NPD process before considerable investment is to be made. This not only reduces the failure rate of NPD and subsequently preventing companies from suffering further economic losses but also helps concentrate efforts and resources on developing other new product ideas which are worthy of additional attention to achieve success. Making a right NPIS decision of selecting the potentially successful new product ideas for further development toward commercialization in the NPD process is the first step to succeed in NPD.

Research efforts spent on the following three areas are obvious. The first area is on identifying various criteria to evaluate new product ideas (Ronkainen, 1985; Tidd and Bodley, 2002; Hart et al, 2003). The second one is on employing the fuzzy theory to deal with linguistics evaluation criteria for the screening evaluation (Hsu *et al.*, 2003; Lin and Chen. 2004; Mohanty *et al.*, 2005; Xu *et al.*, 2007a; Huynh and Nakamori, 2009). The third one is on using scoring and weighing methods to prioritize new product ideas (Henriksen and Traynor, 1999; Linton *et al.*, 2002; Coldrick *et al.*, 2005; Eilat *et al.*, 2008). A detailed discussion is provided in the next chapter. Although these approaches to NPIS are found to be helpful, they can only assist managers in (a) evaluating ideas based on multiple criteria, (b) gathering a suggested value, such as the success level, overall performance score, and level of preference, as a guide for the screening decision, and (c) ranking ideas, followed by distinguishing the best from the worst. These approaches are themselves incapable of certainly making either a go or kill decision for all ideas. They are more for *new product idea* *evaluation* than for *new product idea screening decision making.* NPIS is often inadequately performed using existing approaches. If the optimal cut-off value of the success probability which distinguishes successful ideas from the worthless ones is not determined, managers still face the dilemma of making the exact NPIS decisions among all new product ideas.

B. Not truly listen to the voice of customers in market-driven NPD

Companies today tend to make use of customer-driven management tools, ranging from simple customer surveys and interviews to complicated quality function deployment (QFD), in order to explore and understand customer requirements more broadly and deeply as well as to listen to the voice of customers. Doing so helps companies formulate new products, diagnose the attractiveness of their products, and improve their current products, which are desired by customers.

As assessing customer requirements with regard to the characteristics of a product is a multi-attribute decision making problem, researchers have applied different analytical techniques to support decision making and marketing analysis, thus determining customers' actual needs. Such techniques include a conjoint analysis method employing pairwise comparison (Gustafsson and Gustafsson, 1994), a combination of voting and linear programming techniques (Lai *et al.*, 1998), the employment of an artificial neutral network with a strict requirement on the input variables (Che *et al.*, 1999), the use of the entropy method to convert customer requirements from crisp values to fuzzy numbers (Chan *et al.*, 1999), the application of the analytic hierarchy process (AHP) to convert to fuzzy numbers (Vanegas and Labib, 2001), and so on. There are a number of case studies and applications, in which AHP has been popular and proved to be a powerful tool in weighing the importance of various customer requirements and thus solving decision-making problems of multiple attributes (Armacost *et al.*, 1994; Zakarian and Kusiak, 1999; Chakraborty and Banik, 2006; Lin *et al.*, 2008). However, due to subjectivity of human judgments, as well as vagueness and imprecision inherent in assessing the importance of different customers' opinions, the fuzzy theory has been increasingly employed, or even integrated into the conventional methods to resolve the problem.

In addition to the trend toward using fuzzy numbers as a decision-making tool, a range of literature using the fuzzy theory to study customer requirements have been immense. These studies (Armacost *et al.*, 1994; Chan *et al.*, 1999; Zakarian and Kusiak, 1999; Vanegas and Labib, 2001; Chakraborty and Banik, 2006; Lin *et al.*, 2008), nonetheless, are unusual that they determine customer requirements by commonly making use of the opinions of managers and experts, instead of those of customers. Whether the experts' judgments are able to fully reflect customers' perceptions about the needs of different product characteristics is a matter of dispute. If the voice of customers is not listened to and the customers are not involved in the NPD practices, it is not likely of companies to understand the actual needs of customers and thus develop customer-desired products. This is because only customers themselves understand their actual needs well. Experts cannot read customers' minds but can just guess what the customers need.

C. *Fail to integrate all key influencing factors into a DSS for NPD*

In recent years, many conventional and market-based DSSs for product design and development have been developed (Herrmann *et al.*, 2000; Harding *et al.*, 2001; Khoo *et al.*, 2002; Alexouda, 2005; Xu *et al.*, 2007a). To achieve a competitive edge in a market, companies place greater emphasis on market-based NPD. For this reason, market-based DSSs with regard to NPD are particularly popular in the literature. These studies highlight the key areas that ought to be considered in making decisions on NPD, including customer requirements, customer satisfaction, marketing effectiveness, product quality, product design, and so on. They are mostly related to product attributes, customer behavior, and marketing factors. However, current DSSs mostly consider only a single factor or some mentioned above (Moskowitz and Kim, 1997; Herrmann *et al.*, 2000; Khoo *et al.*, 2002; Alexouda, 2005; Fung *et al.*, 2007; Hung *et al.*, 2008; Liu *et al.*, 2008). For example, Khoo *et al.* (2002) examined the product attributes for customer-oriented NPD but considered customers' demographic information only. Herrmann *et al.* (2000) did consider customer needs, customer satisfaction, and product attributes in NPD, but omitted the marketing factors. A comprehensive DSS taking all these key areas into account at the same time is rarely found.

D. *Fail to take customer satisfaction and customer purchasing behavior into account*

From the modern management perspective, maximizing customer value is the key to surviving fierce competition in the business world. It is logical that the ultimate goal of a company is to create and deliver value to its customers, thereby capturing value from its customers. Hence, many companies actively engage in developing new and attractive products. NPD is a crucial driver which stimulates customers to make purchases and builds relationships between companies and customers. By delivering value through new products, companies satisfy customers and generate profits. The connections among customer purchasing behavior, customer satisfaction, and NPD are apparent. Nevertheless, customer behavior and satisfaction are generally disregarded and excluded in existing DSSs for NPD (see

Table 2.2 in Chapter 2). There are in fact only limited studies (Moskowitz and Kim, 1997; Herrmann *et al.*, 2000) that did include customer satisfaction in DSSs for NPD. Worse still, only one study (Marquez and Blanchar, 2006) is found to have examined customer behavior when developing a DSS for NPD.

E. Calculate the value that customers bring to a company inaccurately

The longer a customer is retained, the higher value he/she brings to a company. Because the acquisition cost of new customers exceeds the retention cost of existing customers by a substantial margin (Dyche, 2002), companies nowadays underline the importance of customer retention and loyalty. Long-term customer relationships are important for companies to sustain business growth, and as a result companies should focus on attracting and retaining customers with a lifetime through NPD, which can make customers attach to companies for long-term and permanent profits.

In the extant literature (Matsatsinis and Siskos, 1999; Wassenaar and Chen, 2001; Alexouda, 2005; Lawson *et al.*, 2006; Kahraman *et al.*, 2007), DSSs normally support NPD decision making on the grounds of profit maximization, transaction-based calculations, and the minimization of cycle time. For example, Hung *et al.* (2008) selected alternatives based on development time and cost when developing an integrated information system for product design. Moreover, based on the maximization of return on investment, Kahraman *et al.* (2007) proposed a decision-making approach for the selection of new products. They indeed fail to take the time value of money into consideration and overlook the future profits generated by a lifelong customer relationship. Existing systems are insufficient and unconvincing in their ability to determine the most profitable NPD projects among alternatives.

1.3 Research Aim and Objectives

Given the above problems, a new and innovative DSS is needed to help companies make more sensible and reliable decisions on NPD, so that companies are able to develop successful and profitable new products which delight customers and thus sustain business growth. More specifically, it is in fact significant to make such decisions at the front end of the NPD process. In reality, NPD process often entails phases and each phase includes one or more decision gates, where managers decide the prospects of new product ideas and NPD projects (see Figure 1.1). Both decision gates of new product idea screening (Gate 1) and NPD project approval (Gate 2), being highlighted in Figure 1.1, at the front end of the NPD process are of paramount importance to the results, either success or failure, of NPD. Making the right decision at these two decision gates could probably minimize the risk of product failure and a waste of resources. Decision making at the front end of the NPD process is then the focal point of this research. This research is hence motivated to respond to the need of a new and effective DSS that can resolve the problems stated previously in Problem Statements A-E. This research therefore aims to improve the effectiveness of NPD decision making and to better satisfy customer needs.

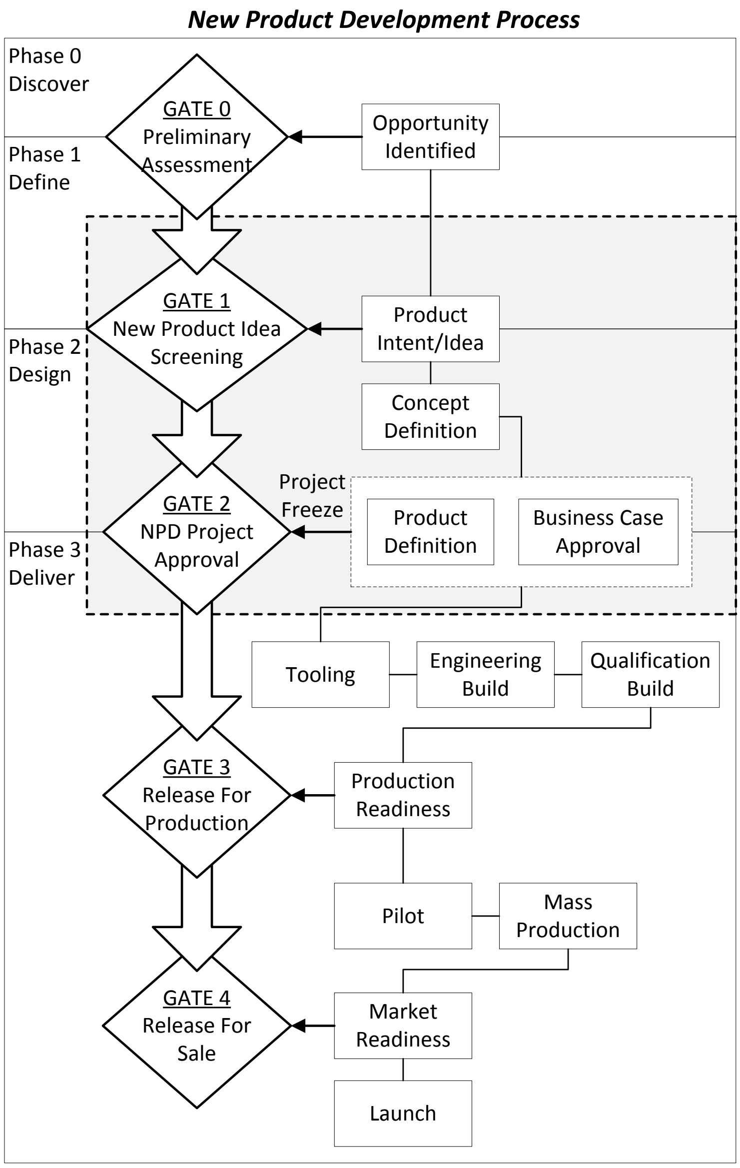


Figure 1.1 NPD process

To achieve the research aim, the key objectives of this research are to:

- Propose a framework of an iDSS for NPD with a consideration of customer satisfaction that supports decision making at the front end of the NPD process;
- Create Module I: an idea screening decision model as an initial evaluation to assess and select new product ideas so that the problem mentioned in Problem Statement A can be resolved;
- Build Module II: a customer perception model to recognize customers' actual needs and prioritize product characteristics that customers desire from the perspective of customers; this module addresses the issue stated in Problem Statement B;
- Devise Module III: a dynamic decision model to aid companies in predicting customer purchasing behavior and estimating the value of customer in the long term; this supports decision-making on new product launch and tackles the problems stated in Problem Statements C-E; and
- Illustrate and verify the three modules of the proposed iDSS using case studies of a power tool company; meanwhile, the feasibility of the proposed iDSS that aids decision-makers in developing successful products to launch is highlighted.

As illustrated in Figure 1.2, three core modules, namely Module I: an idea screening decision model, Module II: a customer perception model, and Module III: a dynamic decision model, are designed to constitute the proposed iDSS. The iDSS denotes that the three modules are joined together into a DSS and they function together as a DSS. Decision makers not only integrate the information needed to support decision making on NPD but also integrate knowledge and judgments from experts of different departments and customers, in order to make the right decision on delivering best-fit products to customers. According to Cohen and Levinthal (1989) and Prencipe *et al.* (2003), such integration has been of growing importance and become essential to business strategies and senior management decision making. In addition, the iDSS could integrate the decisions to be made at gates 1 and 2 at the front end of the NPD process. It is designed and emphasized to operate and aid managers in making NPD decisions at the decision gates of new product idea screening and NPD project approval (see Figure 1.3). It is responsible for evaluating new products and thus supporting decision making at the two gates, i.e., Gate 1: NPIS and Gate 2: NPD project approval. As an initial evaluation, NPIS is firstly performed with the support of Module I to select potentially successful ideas. Module I helps determine pleasing ideas that are to be considered for a detailed evaluation in the next phase. The selected ideas would be further defined and developed as NPD projects. NPD project approval is the next gate to assess such NPD projects and Module III is applied. Reducing the number of alternatives to be developed through the two gates can greatly enable companies to concentrate on the selected projects as well as to reduce the risk of investing in time-consuming and costly ideas and projects, so that the success rate can be maximized. Some ideas selected at Gate 1 using Module I are perhaps ineligible for investment after further evaluation is made at Gate 2 with the support of Modules II and III. Module II, which explores customers' perceptions on new products, has two functions. One is to support decisions to be made in Module III by inputting the relative importance weights of product characteristics for evaluation. Another function is to provide managers with valuable information regarding customer requirements for generating better and customer-oriented ideas.

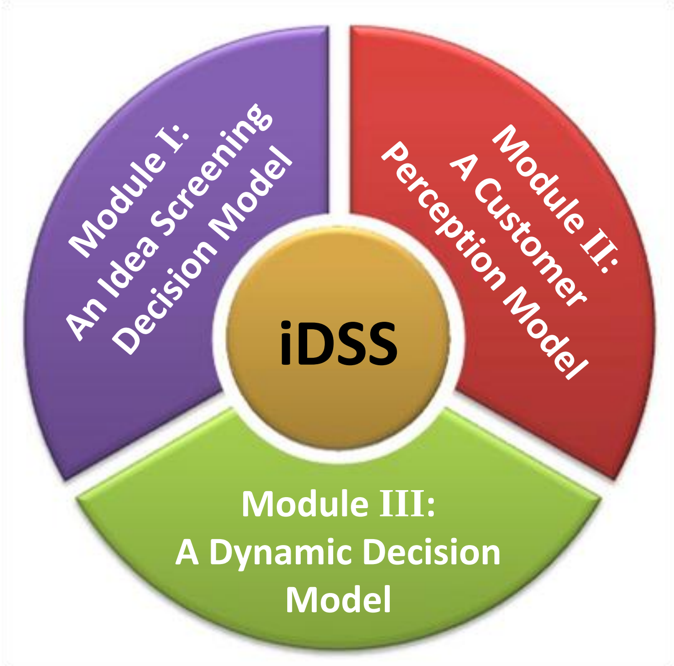


Figure 1.2 Proposed integrated decisions support system (iDSS)

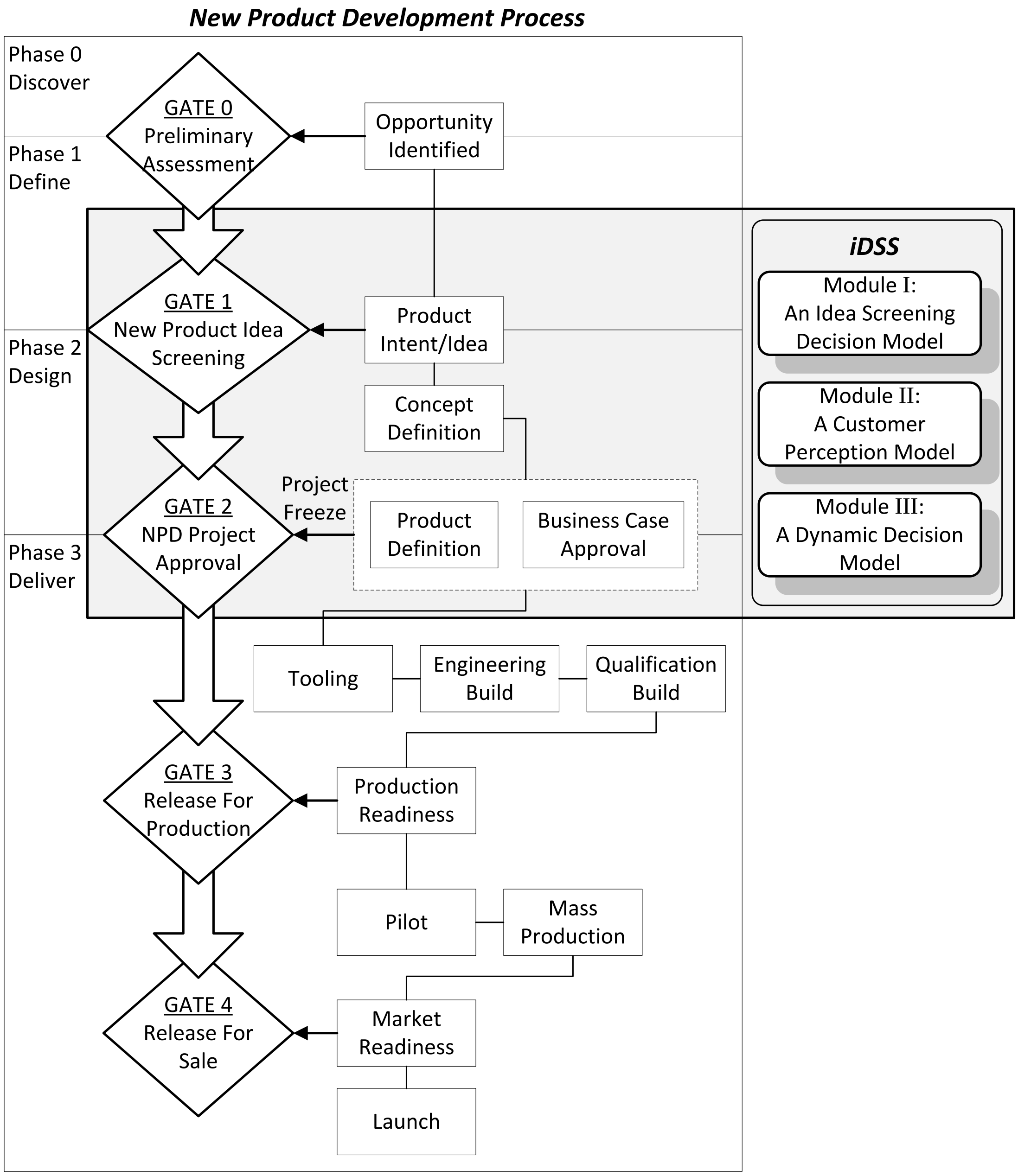


Figure 1.3 Proposed iDSS at the front end of the NPD process

Each module in the proposed iDSS has its specific purpose. Module I is designed for NPIS, Module II is to weigh and prioritize product characteristics from the perspective of customers, and Module III supports decision making regarding NPD project approval as well as the formulation of NPD and marketing strategies. These three core modules are linked but they resolve specific problems individually. The framework of the proposed iDSS is shown in Figure 1.4. The proposed iDSS integrates both qualitative and quantitative data. It serves as a decision aid and is beneficial to companies in the following manner:

- *Module I: an idea screening decision model*

  Module I of the proposed iDSS is intended to include and develop an idea screening decision model. In regard to Problem Statement A given earlier, there is a need for investigating a new approach to make the exact NPIS decisions. This creates a great opportunity to develop Module I as a part of the proposed iDSS in this research. This module does not only distinguish between the best and the worst, but also provides the exact go or kill decisions that the managers should make. As illustrated in Figure 1.4, this module can help managers use multiple criteria to evaluate new product ideas and help them determine the success probability of each new product idea. As a result, better NPIS decisions, i.e., either a go or kill decision, can be made on all new product ideas. It therefore prevents companies from investing in uncertain and worthless new product ideas, and instead helps managers select the better new product ideas for further development. In this regard, this research makes contributions in enhancing the NPD success rate in the industry.

- *Module II: a customer perception model*

  This research focuses on customer-driven NPD. The voice of customers about product characteristics is important. However, with reference to the literature, researchers mostly determine the relative importance weights of customer requirements based on experts' judgments (Kwong and Bai, 2002; Kong and Liu, 2005; Wang *et al.*, 2007; Duran and Aguilo, 2008; Tseng *et al.*, 2008) rather than customers' preferences. Hence, a customer perception model is required to address the issue stated in Problem Statement B, thereby introducing Module II in the proposed iDSS. It is to assemble customers' opinions, and then to weigh and prioritize product characteristics that customers desire from the perspective of customers (see Figure 1.4). This module enables companies to recognize customers' actual needs and then to place greater emphasis on particular product characteristics for NPD and improvement. This can facilitate companies to penetrate the market and grow sustainably, for new or enhanced products can initiate purchasing actions and fulfill customers' actual needs.

- *Module III: a dynamic decision model*

  A dynamic decision model for NPD project approval and for formulation of both NPD and marketing strategies is included and acts as Module III of the proposed iDSS. This module is designed to tackle the problems mentioned in Problem Statements C-E. According to Figure 1.4, Module III consists of two sub-models: a customer purchasing behavior model (sub-model 1) and a net customer lifetime value (NCLV) estimation model (sub-model 2). Sub-model 1 provides a comprehensive picture of the interrelationship among product, customer, and marketing influencing factors, addressing the issue stated in Problem Statement C. It also takes customer satisfaction and customer purchasing behavior into account to resolve the problem mentioned in Problem Statement D. In addition, customer purchasing probabilities are also determined to act as inputs for sub-model 2. Sub-model 2 is linked to sub-model 1, in which a unique equation to calculate NCLV is formed; this resolves the problem discussed in Problem Statement E. This module enables companies to predict customer purchasing behavior and estimate NCLV in the long term. This can help managers not only compare alternatives of NPD projects and determine which project will be most valuable to launch, but also better understand customer behavior toward a particular product and determine the kinds of marketing strategies that should be adopted for the new product. It also enables managers to build confidence of making better decisions with the support of this decision aid and reach a consensus among people from multiple functions, collating and analyzing up-to-date information on the market and product attributes to improve NPD and generate new product ideas for future investment.

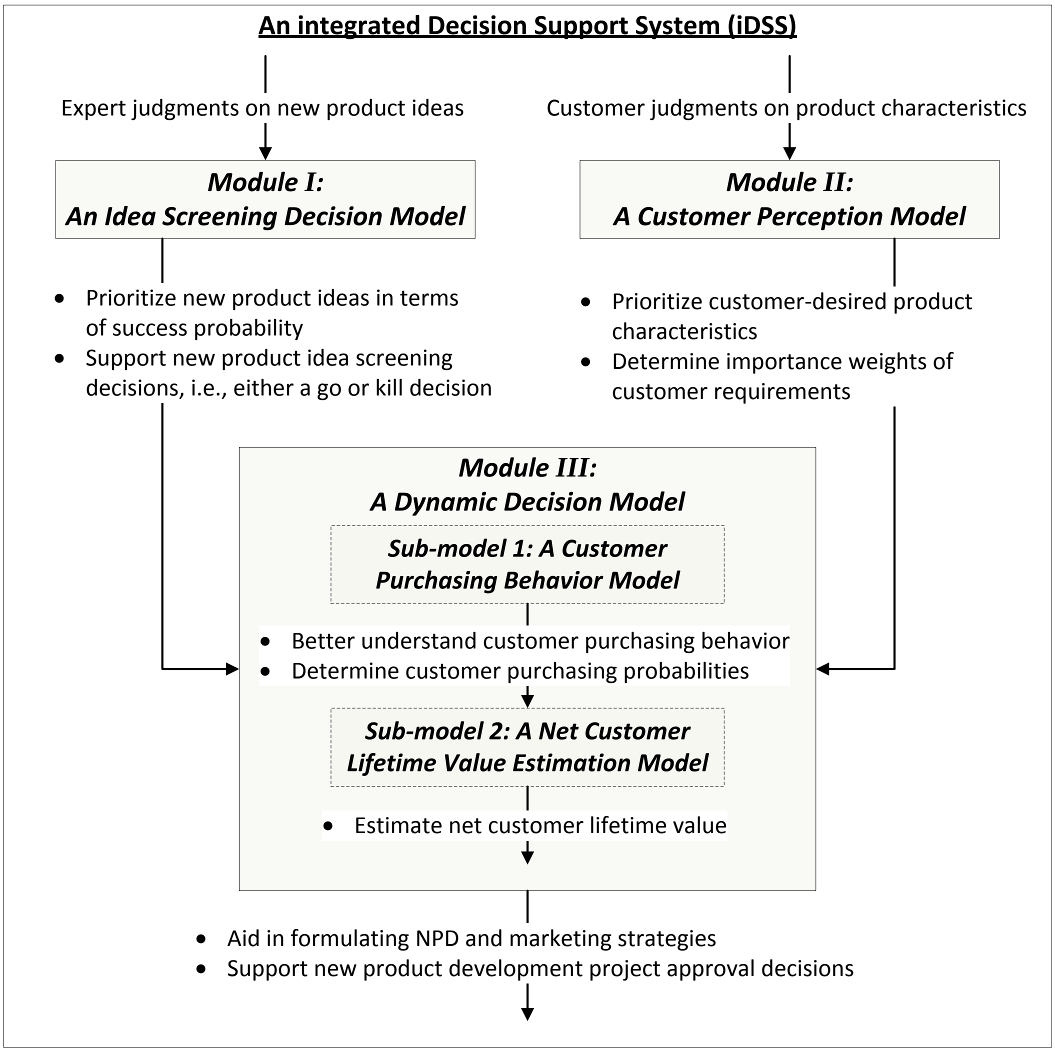


Figure 1.4 Detailed framework of the iDSS

1.4 Research Methodology

A mixed approach is adopted in this research. Qualitative and quantitative methods are combined (Greene *et al.*, 1989; Tashakkori, 1998; Johnstone, 2004; Protheroe *et al.*, 2007) and used to develop the proposed iDSS in this research. The former includes case studies and interviews while the latter embraces a survey as well as quantitative modeling and analysis. This mixed approach using both qualitative and quantitative data adds value to the harmony of the proposed iDSS and provides the iDSS with a more complete and full picture. A diagram regarding the methodology of this research is shown in Figure 1.5. The picture indicates that methods including interviews, a customer survey, the scorecard technique, Markov analysis, the fuzzy analytic hierarchy process, and system dynamics are used in the development of the proposed iDSS while case studies are carried out to apply and validate it. Data collection from the case company is definitely required to support the establishment of the proposed iDSS. The schedule of this research is attached in Appendix A. The methods employed are discussed in detail below.

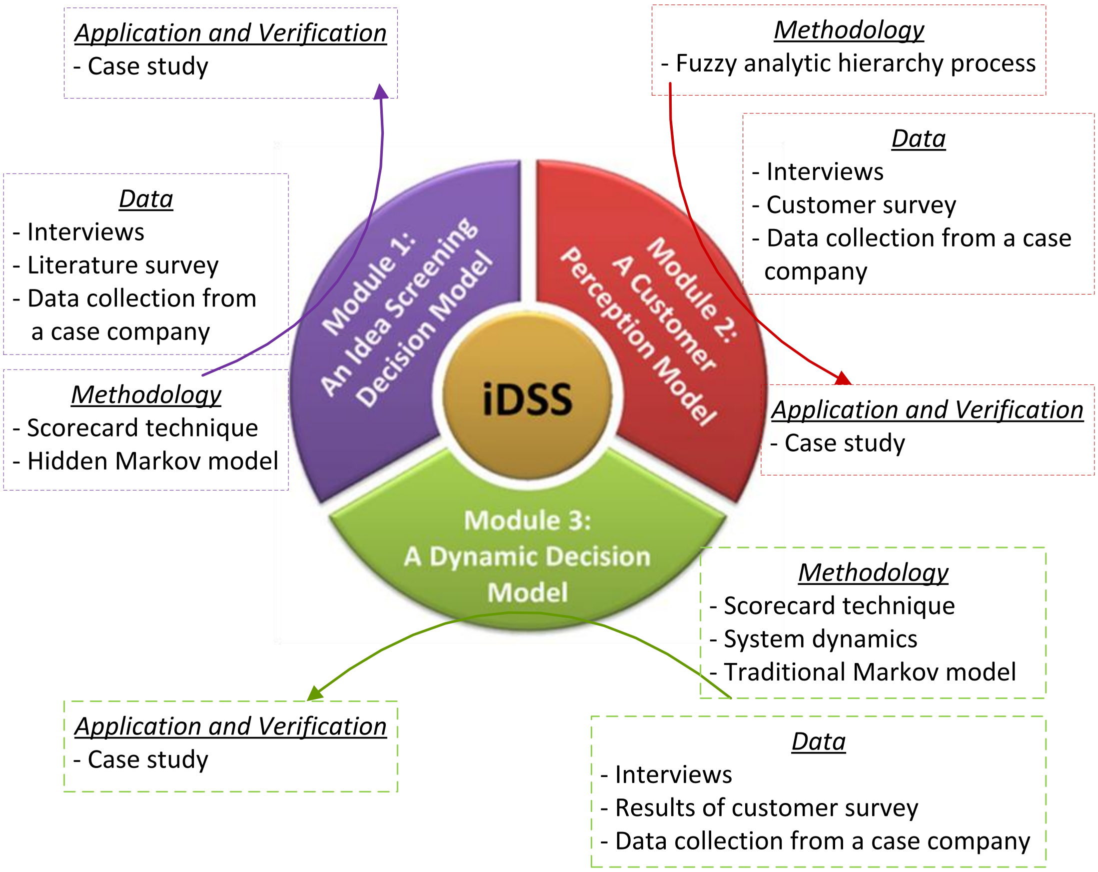


Figure 1.5 Research methodology

Qualitative Methods

A. Case Studies

With reference to the literature, it is extremely common and credible for researchers to use case studies or case examples to illustrate the effectiveness and feasibility of their DSSs and approaches to NPD (Milling, 1996; Moskowitz and Kim, 1997; Herrmann *et al.*, 2000; Kengpol and O'Brien, 2001; Chen *et al.*, 2002; Alexouda, 2005; Xu *et al.*, 2007a; Xu, *et al.*, 2007b; Hung *et al.*, 2008). For example, Kengpol and O'Brien (2001) gathered data from a business that markets hi-tech products as a pilot study to validate the suggested DSS while Xu *et al.* (2007a) used design alternatives of new products from a company as a case example to illustrate the application of the DSS for product design in concurrent engineering. Other methods adopted in the NPD domain are absolutely hard to be found. Therefore, it is reasonable to take advantage of case studies to demonstrate and verify the value of the proposed iDSS in this research. As the proposed iDSS consists of three modules and each module serves specific purposes, a case study is used to illustrate the application of each module and the feasibility of each module is then verified and highlighted.

The case studies are a part of the Teaching Company Scheme (TCS), which is a collaboration of the Hong Kong Polytechnic University and a case company, and is supported by the HKSAR Government's Innovation and Technology Commission. The case studies are related to the specific needs of the case company, who can utilize the results and benefit from this research.

Both qualitative and quantitative data used for the three case studies were actually obtained from the case company. The case company was found in 1985. A listed company in Hong Kong, the case company is a world-class leader in innovative electrical products, particularly power tools, with a high value and powerful brands. Its products are marketed to individual households as well as the home improvement and construction industries worldwide. In 2009, it launched over 300 new products which caused the sales to be up by one-third. With sophisticated marketing plans and strategic focus on cutting-edge products, the case company achieves success in this highly intensified marketplace, making a strong net profit growth of 180.7% in 2009. The case company is famous for its power tools, which are thus particularly chosen to be examined in this research. Since a wide range of data was required for each module, the details of these data are not described here but will be given in the respective chapters later (see Chapters 3-5).

B. Interviews

A group of NPD experts from the case company were invited to in-depth interviews in this research. The interviewees are the directors from the functions of quality, marketing, engineering, manufacturing, and supply chain. They are the key decision-makers who are responsible for screening new product ideas and approving competitive and worthy NPD projects. Such interviews are to better understand the NPD process and the NPD practice of the case company, as well as the key considerations of NPD, thereby enriching the knowledge to develop a novel iDSS in this research. Experts' judgments were also used to support and confirm the development of the proposed iDSS, such as the development of scorecards with clear definitions, the establishment of a hierarchical structure of product characteristics, and the evaluation of new product ideas and NPD projects.

Quantitative Methods

A. Customer Survey

A customer survey was conducted to explore customers' perceptions of new products by investigating how customers evaluate the products (i.e., power tools in this research) and see how they decide to buy them. As power tools from the case company are particularly famous, they are chosen to be examined in the customer survey. The survey using pairwise comparison was designed and its results were analyzed using the fuzzy analytic hierarchy process (FAHP) approach. A sample of the questionnaire used in the customer survey is attached in Appendix B for reference. 150 questionnaires were randomly distributed in August 2008 to a sample of customers who had experience of buying power tools from the case company. 102 of the questionnaires were returned and completed properly. These primary data were then gathered and used in this research. This customer survey using pairwise comparison was designed and used to collect customers' judgment so as to capture the actual voice of customers directly. This helps companies gain a deeper understanding of customers' actual needs with regard to power tools, instead of gaining it through estimations made by experts. The data of the customer survey were used in Module II of the proposed iDSS.

B. *Quantitative Modeling and Analysis*

The four following methods, which are parts of quantitative modeling and analysis, are employed in this research to support decision making.

- The fuzzy analytic hierarchy process

  When developing new products, companies may find it difficult to prioritize the customers' actual needs that are corresponding to product characteristics, as such prioritization constitutes a complicated decision-making issue that involves the consideration of multiple attributes. This challenge is also faced by the case company. FAHP is composed of AHP and the fuzzy theory, and is a multi-attribute decision-making technique that is effective. It is recommended in tackling complex problems and simultaneously dealing with the ambiguity and fuzziness of human judgments. This is supported by many researchers (Lai and Hwang, 1994; Liang and Wang, 1994; Gogus and Boucher, 1997). FAHP has been popular to be used to deal with the matters related to NPD; for example, Xu *et al.* (2007a) employed the fuzzy theory to evaluate product design alternatives of new products, while Kwong and Bai (2002) used FAHP to determine the importance weights of customer requirements in QFD. Other applications of FAHP can be easily found in the literature (Buckley, 1985; Cheng and Mon, 1994; Chen, 2000; Csutora and Buckley, 2001; Mikhailov, 2003; Lau *et al.*, 2006). Therefore, FAHP is considered an appropriate algorithm to be applied. In this research, FAHP is to (a) analyze customers' judgments using the data of the customer survey, and subsequently to (b) determine and prioritize the relative importance weights of customer requirements, which correspond to product characteristics. This would help companies launch more attractive and competitive products, thus better satisfying their customers. FAHP is employed to construct Module II of the proposed iDSS. Further discussion on FAHP can be found in Chapter 2.

- The scorecard technique

  A scorecard is a critical and practical management tool for performance measurement (Phusavat *et al.*, 2009). To evaluate the performance of new product ideas and product attractiveness as well as to quantify linguistic judgments for measurement, the scorecard technique is applied in this research as a strategic tool of performance measurement. The scorecard is mainly attributed to its simplicity as well as its flexible and effective nature. Two specific scorecards are designed to help managers measure the performance of new product ideas, and assess the attractiveness of NPD projects. Developing the scorecards is one of the most important parts for the establishment of the proposed iDSS. A specific evaluation scorecard to assess new product ideas is constructed in Module I of the proposed iDSS. Another scorecard which assesses the attractiveness of NPD projects is developed in Module III.

- Markov analysis

  Markov analysis is one of the mathematical techniques for sequential decision making under uncertain circumstances. It deals with the probabilities of future occurrences by analyzing presently known probabilities (Render *et al.*, 2006). Markov analysis makes use of the transition probabilities matrix, which is regarded as the Markov process, to illustrate the probability that the system will change from one time period to the next, and to predict future states or conditions. Markov analysis is employed in this research as it is a flexible and sophisticated method in tackling decision-making problems (Isaacson and Madsen, 1976; Puterman, 1994). There are two kinds of Markov models, which differ from each other on the features of states in the Markov process. The details of Markov analysis entailing the traditional Markov model and hidden Markov model (HMM) are given in Chapter 2.5.2 while the reasons of adopting these two kinds of Markov models are given below.

Traditional Markov model: Traditional Markov model refers to the fundamental theory of Markov analysis. Traditional Markov model contains an infinite number of states, which are visible. Studies which apply traditional Markov model to decision making, particularly those related to marketing and customer behaviors, are common. For instance, Pfeifer and Carraway (2000) built a Markov model concerning customer relationships, and Burez and Van-den-Poel (2007) estimated the churn probability for marketing actions through a Markov model. Due to its feasibility, traditional Markov model is employed in this research. It is considered a suitable and reliable technique to model customer purchasing behavior and to predict the long-term NCLV in sub-model 2 of Module III.

Hidden Markov model: Unlike the traditional Markov model, HMM contains a finite number of states, which are unobserved or hidden. HMM is a powerful stochastic and statistical technique, which is strongly capable of explaining the occurrence of observations. Resembling the traditional Markov model, it is also useful in solving decision problems which involve risks (Sonnenberg and Beck, 1993). The application of HMM is widespread. For example, HMM serves as a predictor or classifier for information retrieval (Miller *et al.*, 1999) and extraction (Freitag and McCallum, 1999; Seymore *et al.*, 1999), text classification (Yi and Beheshti, 2009), and stock marketing forecasting (Hassan and Nath, 2005). Owing to its characteristics as well as strong mathematical and theoretical foundation, HMM is deemed suitable for addressing the issue of NPIS. It is thus employed in Module I of the proposed iDSS in this research to predict the overall performance of new product ideas in terms of success probability.

- System dynamics

  System dynamics, which can be used for system modeling and computer-based simulation, is a valuable aid in gaining insights into the complex feedback systems and making appropriate decisions (Lin *et al.*, 1998). Decision making in NPD often involves abundant information while customer purchasing behavior is complicated but closely related to the outcome of NPD. System dynamics is found to be appropriate in this research for the sake of modeling and simulation. Further discussion on system dynamics is given in Chapter 2.

Having all the features of system dynamics, iThink® application was used to develop Module III: the dynamic decision model in this research. iThink® is chosen in this research on account of its remarkable features. Its building blocks approach and visual appeal make it easy for both experts and practitioners to construct their models and carry out simulations with many different variables under a variety of circumstances (Ray, 1994; Pendergraft *et al.*, 2005). With a systems thinking framework, iThink® can make a major contribution to improve the quality of models and the reliability of simulations. It can also improve the effectiveness of the models, through which the users can have higher initiative to improve the performance (Isee System Inc, 2004).

Sub-model 1 of Module III was developed by iThink®, and is capable of predicting customer purchasing behavior based on three different types of information: product attractiveness, customers' preferences and customer satisfaction, as well as marketing strategy. Besides, it provides a comprehensive picture for managers to better understand the interactions among all elements that are considered in NPD decision making. As this sub-model is dynamic, it offers opportunities for managers to test various scenarios of customer behavior when purchasing a specific product, so that business planning and strategy formulation can be improved.

1.5 Outline of This Thesis

This thesis consists of six chapters and is structured as follows:

Chapter 1 is an introduction to this research. The background of this research is firstly given, and then the problem statements which motivate this research are specified. The research aim, objectives, and methodology are identified and described. In brief, this research attempts to propose an iDSS to respond to the need of a new and innovative DSS at the front end of the NPD process. Lastly, a summary of the six chapters in this thesis is presented.

Chapter 2 offers an important foundation of the development of the proposed iDSS in the subsequent chapters. Relevant literature about NPD, NPIS, DSSs regarding NPD, as well as various decision-making tools and techniques are examined and discussed. The linkage between NPD and customers is discussed in terms of the value creation and capturing process, customer satisfaction, and customer relationships. The literature survey provides evidence and supports to establish the theoretical framework of the proposed iDSS. It also highlights the significance of this research.

Module I of the proposed iDSS is to evaluate new product ideas and thus to facilitate the NPIS decisions made from the perspective of experts. Chapter 3 describes the framework of Module I, and is followed by its development. Six criteria to evaluate new product ideas are defined in Module I. A scorecard to assess new product ideas is introduced. An HMM to determine the success probability of each new product idea is developed after that. A case study is discussed to verify and highlight the feasibility of Module I.

Module II of the proposed iDSS is to evaluate new products from the perspective of customers for the sake of prioritizing product characteristics. Chapter 4 provides a detailed explanation of the steps to assess the relative importance of customer requirements, which are corresponding to product characteristics. A hierarchy, concerning product characteristics is defined for analyzing customers' perceptions. The results of the customer survey showing customers' perceptions on product characteristics and the algorithm of FAHP are also presented. A case study is carried out to illustrate how Module II can help companies prioritize customer requirements.

Module III of the proposed iDSS explores customer purchasing behavior and NCLV is estimated for NPD project approval and strategy formulation. Chapter 5 describes the framework of Module III, and then turns to discuss the development of Module III, in which system dynamics is applied. A discussion of sub-model 1, which demonstrates customer purchasing behavior, is offered. All influencing factors, be it key product-related, customer-related, and marketing-related, affect the customer purchasing behavior. The customer purchasing probability is then predicted. Next, the estimation of NCLV, known as sub-model 2 in this thesis, is introduced. Markov analysis and the equation of NCLV are incorporated and explained. The NCLV for each NPD project can be calculated to aid managers in making NPD approval decisions and formulating both NPD and marketing strategies. This chapter is concluded by a case study which applies Module III to the NPD project approval.

Chapter 6 concludes the thesis by summarizing the research findings. Contributions made by this research are identified. To perfect this research and extend it, limitations of this research and suggestions for future research are presented.

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

Due to the importance of new product development (NPD) and its close linkage with customer satisfaction, this research proposes an integrated decision support system (iDSS) in these two domains. The framework of the iDSS has been introduced in the previous chapter. The background, aim, objectives, and methodology of this research have also been discussed, followed by the outline of this thesis.

As this research focuses on decision making at the front end of the NPD process, literature regarding NPD, new product idea screening (NPIS), and decision support systems (DSSs) for NPD is firstly discussed in this chapter. The deficiencies of current DSSs for NPD are highlighted along with the values of the proposed iDSS. Decision-making tools and techniques that have been mentioned earlier are then described in detail.

2.2 New Product Development

2.2.1 Importance of New Product Development

Nowadays, there are different definitions and perceptions when "NPD" is concerned. In the most general sense, it refers to either products, services, processes, or technologies which are new and innovative to the world. Indeed, NPD refers to the exploitation and introduction of new ideas for practical applications or commercial objectives (Melissa, 2005).

New technologies, innovation, hyper-competition, fast-paced economy, and so on are all the characteristics of the dynamic market with intensified competition nowadays (Drejer, 2002). Successful NPD is the key to success for companies, and it helps companies maintain their competitive advantages and positions in the marketplace. According to the study (Smith, 2006), the most superior competitive advantage of 75% of the fastest growing companies is to introduce products, services, and business processes that are both unique and distinct to the market. Additionally, a survey (James, 2006) indicated that about 90% of companies give priority to NPD in their business strategy for 2004 and the years onward. These prove that in a dynamic environment, NPD is of paramount importance for business growth in every business practice in all sectors.

Apart from the spark of new technological revolutions, the success rate of NPD is extremely low due to the effect of innovation funnel (see Figure 2.1) (Stevens and Burley, 1997). Hence, many researchers around the world have studied the best practice of NPD for driving sustainable business growth and success by means of developing and extending competitiveness and achievement in the global markets (Momaya and Ajitabh, 2005).

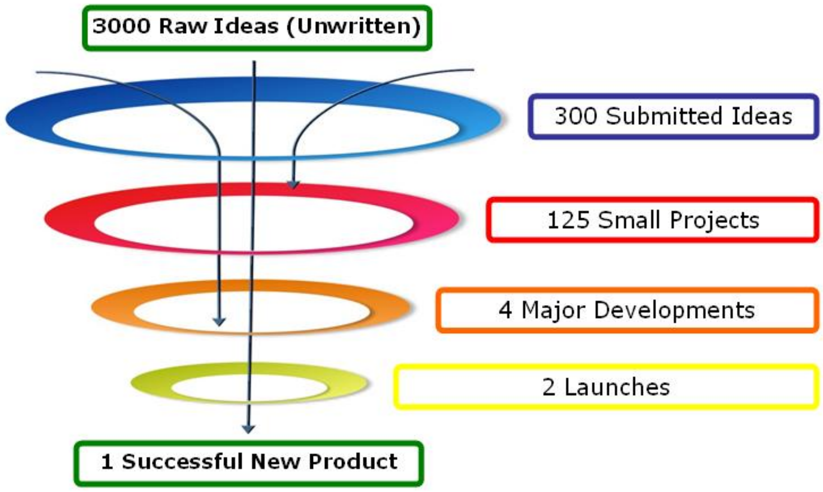


Figure 2.1 Innovation funnel

To maximize the success rate, a robust NPD process is the crucial solution (Hung *et al.*, 2008). Companies have to design a sophisticated and effective NPD process, ranging from idea creation to product launch, which often involves cross-function integration and complicated interdisciplinary activities. Discussion on the NPD process is given later. More importantly, companies have to take dynamic customer needs and their satisfactory level into account for successful NPD (Melissa, 2005), which is explored afterward. An effective and robust NPD is beyond doubt essential for business growth and success. This research establishing an iDSS for NPD with a consideration of customer satisfaction is therefore crucial and thus initiated.

2.2.2 Customer Satisfaction, Customer Relationships, and the Value Process in NPD

Customer satisfaction is fundamental. It is expressed by customers' experience of using a purchased product and customers' expectations on the fitness of a particular product for its intended purpose (Herrmann *et al.*, 2000). As stated by Hanan and

Karp (1989), the ultimate objective of every business is to satisfy customer needs and drive customers to do business. Customer relationships will be established if customers are satisfied. According to the study (Ravald and Gronroos, 1996, p.19), "the ability to provide superior value to customers is a prerequisite when trying to establish and maintain long-term customer relationships." The "value" refers to the value received by the customers, at the time of purchasing the product and after using it (Oh, 1999). It is evident that launching new products to deliver value to customers is a crucial driver of customer satisfaction. This explains why companies actively engage in developing new products to delight customers by fulfilling their needs, or even exceeding their expectations. The development and delivery of customer-driven products are of paramount importance for instilling value in customers. By delivering value through new products, companies satisfy customers and generate profits through building customer relationships, forming a value creation and capturing process. The value process demonstrates that two important business activities, namely promoting customer satisfaction and developing new products, are associated. They are both indispensable in operating a business. Successful NPD that maximizes customer value is the key to surviving fierce competition in the market.

Customer satisfaction is greatly significant in building and retaining profitable customer relationships, and it is closely linked to the commercial success of NPD. It is in fact the basic necessity of customer relationships. Once a new product successfully fulfills customer needs, customers are satisfied and then the customer relationships are established. However, companies still have to endeavor to delight their customers and exceed customers' expectations to result in a higher level of satisfaction. Only in such a situation, customer loyalty can be built considerably and rigidly. It has been empirically established that customer satisfaction leads to customer loyalty and, in the long term, to profitability (Heskett *et al.*, 1994; Murphy *et al.*, 2005). Satisfied customers demonstrate greater willingness to pay more for new products and to purchase in larger quantities; their repeated purchasing behavior would secure a permanent sales basis for a business. Besides, satisfying customers can instill value in a business to gain sustainable competitive advantages so that the core competences of a business can be exploited through NPD. This suggests that customer satisfaction is relevant to the prospects and success of a business and plays a key role in business growth. More importantly, customers with longer lifetime and higher loyalty are more profitable to a company (Dyche, 2002; Jain and Singh, 2002). Companies could probably expand profitability and grow their business by delighting, acquiring, and retaining such kind of customers. Satisfying customers through NPD and thus forming lifelong relationships with them is valuable for a company to gain permanent profits and to sustain business growth.

Customer relationship management (CRM) is a core relationship marketing tool which delivers better customer value, so that customers are satisfied through new products (Cronroos, 2000). CRM is a philosophy that anticipates customer needs with the purpose of providing the target customers with the right product, at the right time, in the right place (Yourdon, 2000). It in fact includes both marketing and customer considerations. It becomes increasingly important in all kinds of businesses to sustain long-term growth in today’s competitive environment. Companies are therefore motivated to adopt CRM in order to respond rapidly to customer needs. This is because the acquisition cost of new customers exceeds the retention cost of existing customers by a substantial margin (Dyche, 2002). Moreover, satisfying customer needs can retain customers and build customer loyalty, as well as enhance the market share and gain a better beneficial position in the market. CRM would result in significant financial returns (Rust and Zaborik, 1993; Chen *et al.*, 2004a; Ip *et al.*, 2006). Keh and Lee (2006) and Meyer (2007) also agreed that CRM greatly assists companies in gaining more profits by giving customers incentives to build lifelong loyalty. In fact, developing customer relationships is the key activity of value creation in today's business strategy, while pursuing long-term customer relationships is the ultimate goal of many companies. NPD is an important approach to develop customer relationships. The effort to create and deliver products that the customers desire is therefore essential to enable companies to capture value, i.e., profits and market share, in return and remain competitive. In terms of management, CRM would help companies plan their NPD and design appropriate marketing strategies for the sake of customer acquisition and retention.

All in all NPD is the key driver to delight customers by fulfilling their needs while customer satisfaction is crucial in business growth and profits as it is the basic necessity of developing good customer relationships. The value process, in which companies deliver value to customers through new products and capture value from customers in return, is crucial. Satisfying customers for lifelong relationships could probably magnify the value created and captured in the value process. The concepts of the value process, customer satisfaction, and customer relationships, all being part of the philosophy of CRM, are found to be vital in NPD and thus applied in this research. "CRM" in this thesis refers to these three concepts. Incorporating the perspective of CRM into NPD by proposing an iDSS is therefore the main concern in this research. Besides, the failure of NPD projects is often attributed to not satisfying customers' actual needs, and to overemphasize financial considerations rather than marketing criteria when making NPD decisions. CRM, as mentioned above, is important to solve the problem. Involving customers in NPD is hence essential. This leads companies to focus on NPD projects which better fit customers' actual needs. The decision making in NPD should therefore focus not only on the attractiveness of a new product to customers but also other considerations regarding customers and marketing.

2.2.3 New Product Development Process

The NPD process is necessary in the practice of NPD as mentioned beforehand. It differs from company to company but generally starts from idea generation and ends with product launch, translating intangible ideas to tangible physical assets. Rosenthal (1992) defined an NPD process in terms of four stages: idea generation and concept design, definition and specification, prototype and development, and commercialization. Cooper (2000) developed a five-stage process: project scoping, building business case, product development, testing and validation, and launch. Crawford and Di-Benedetto (2002) suggested three generic stages: redevelopment, development, and commercialization. Swink and Song (2007) indicated four basic stages: business/market analysis, technical development, product testing, and product commercialization.

The NPD process is usually implemented as a stage-gate process for better decision-making practices (Cooper, 1990a; O'Connor, 1994; Phillips *et al.*, 1999; Cooper *et al.*, 2002; Cooper, 2008). Stage-gate is a methodology to manage the NPD process, and it divides the process into various stages with a set of activities. A gate is located after each stage and is regarded as a checkpoint of quality control or a decision point. Inputs, judgment criteria, and outputs vary among gates. NPD projects could open the gate and move to the next stage only if they pass the defined criteria of the current gate. As NPD is a multidisciplinary division, managers from multiple functions or business units would often act as gatekeepers to review, assess, and approve the projects as well as to allocate necessary resources. A typical stage-gate process is illustrated in Figure 2.2.

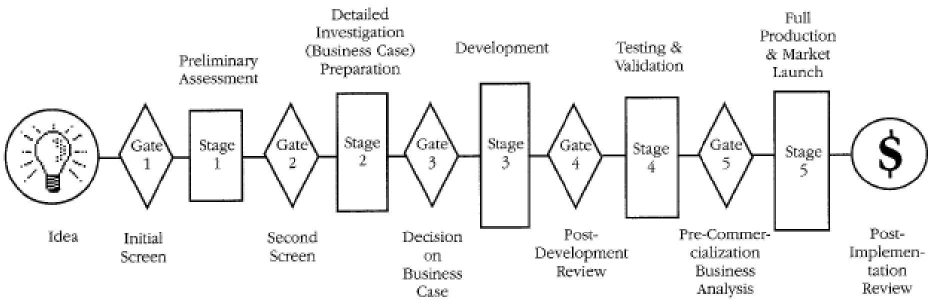


Figure 2.2 Typical stage-gate process (source: Cooper, 1990a)

Although the NPD process varies, it is important to have screening decisions in the NPD process to eliminate new product ideas and NPD projects that are potentially inferior and worthless before detailed engineering, mass production, and commercialization. Decision gates are often not limited to one but in a great varieties in the NPD process. They help prevent companies from investing unrecoverable money, time, and resources on NPD and help minimize the risk of losing money by launching worthless products. In other words, the first step to succeed in NPD is the decision making, which selects favorable ideas and approve profitable NPD projects to be further invested. Costs often increase dramatically in the NPD process. Meanwhile, companies are unlikely to terminate ongoing projects (Balachandra, 1984; Schmidt and Calantone, 1998).

Accordingly, there is a great necessity to eliminate new product ideas and NPD projects that are inferior as early as possible at the front end of the NPD process before considerable investment is made. This not only reduces the failure rate of NPD, subsequently preventing companies from having further economic losses, but also helps manipulate both efforts and resources to focus on developing other NPD projects that are worthy of additional attention and that are likely to achieve success. Right decisions should be made to select new product ideas and NPD projects that are profitable before developing and commercializing them, for this is essential to achieve success in NPD. This research therefore has three focuses. The first focus is to tackle decision making at the front end of the NPD process. The second focus is to aid companies in making proper decisions before the stages of production and commercialization. The third focus is to support screening decisions on new product ideas and NPD projects, as well as decisions on both NPD and marketing strategies.

With reference to the literature, in order to survive and succeed in the current business environment, companies usually focus on several ways to improve their NPD, such as identifying customer needs for continuous NPD (Melissa, 2005; Liu *et al.*, 2008), improving product quality (Kwong and Bai, 2005; Swink *et al.*, 2006), and accelerating the NPD process toward commercialization (Melissa, 2005; Swink *et al.*, 2006; Xu *et al.*, 2007a). Numerous DSSs are available in the literature that aid product classification (Mohanty and Bhasker, 2005), single product design (Balakrishnan and Jacob, 1995; Mohan *et al.*, 2007; Xu *et al.*, 2007a), product line design (Zha *et al.*, 2004; Alexouda, 2005; Kumar *et al.*, 2007), and market-based product development (Moskowitz and Kim, 1997; Herrmann *et al.*, 2000; Harding *et al.*, 2001; Chen *et al.*, 2002; Khoo *et al.*, 2002; Alexouda, 2005). However, a systematic way that takes NPD, customers, and marketing considerations into account should be developed, so that an effective decision can be made in the NPD. However, such a process is currently lacking. There are five major gaps in the contemporary literature, and they have been identified as Problem Statements A-E discussed previously (see Chapter 1).

2.3 New Product Idea Screening

2.3.1 Challenges to Make New Product Idea Screening Decisions

NPIS is a stochastic problem involving risk and uncertainty. Managers often encounter difficulties in making appropriate and convincing NPIS decisions in an objective and definite manner. NPIS decisions made at the early NPD stage is to evaluate which new product ideas are worthy of further investment in terms of the expected market response and the internal proficiency in developing such ideas. In other words, they aim to predict the probability of whether the new product ideas would succeed, so that they can make go or kill decisions. Such decision-making process often involves the following four difficulties.

A. *Lack of information or little reliable information available:*

The accuracy of such decision making is dependent on the availability of information about the new product ideas. However, the process of acquiring information is difficult. The inadequacy of sufficient and concrete information is a common problem of NPIS (Rochford, 1991; Hsu *et al.*, 2003; Mohanty *et al.*, 2005). Even if there is enough information available, it is often vague and incomplete at the time of decision making, and some of the information is even unquantifiable.

B. *Highly uncertain environment:*

The external environment characterized by fast-changing market needs and rapid technological innovation makes NPIS decisions unreliable as time goes by. New product ideas to be further developed hardly reach managers' expected performance in such a highly uncertain environment.

C. *Conflicts and disputes over NPIS decisions:*

NPD is a multi-disciplinary activity in which cross-functional project teams are increasingly involved nowadays. Over 76% of companies adopt this strategy (Page, 1993). Individuals with different backgrounds, competencies, responsibilities, and interests speak different languages (Brereton and McGarry, 2000). Therefore, it is natural that conflicts and disputes regarding NPIS decisions generally result from expertise from multiple departments with different perspectives.

D. *Subjective and inaccurate judgments:*

Making NPIS decisions probably depends on experts' experience and intuition, which are subjective and inaccurate. Some researchers (Haque *et al.*, 2000; Linton *et al.*, 2002; Gidel *et al.*, 2005) have criticized the inability of managers to judge new product ideas accurately owing to their limited experience of only some NPD projects. The uncertainty in making right NPIS decisions caused by this, therefore, has to be addressed.

2.3.2 Current Approaches to New Product Idea Screening

Approaches that support screening decision making have been developed to the aforementioned difficulties over the years. NPIS decision making is generally considered a multi-attribute or multi-criteria decision-making procedure that requires a comparative evaluation of new product ideas. A range of studies concerning "new product introduction," "project selection," "product idea screening," and so on is present. It is discovered that current studies can generally be classified according to the following foci.

- *Identification of various criteria, including risk factors, to evaluate new product ideas* (Ronkainen, 1985; Tidd and Bodley, 2002; Hart et al, 2003):
  In general, multiple factors such as development cost, marketing competence, production capability, business objectives, process effectiveness, lead time, profits, customer requirements, demand, as well as risk or uncertainty have been taken into account to evaluate the performance of new product ideas and NPD projects for screening decision making by many authors (De-Brentani and Droge, 1988; Melissa, 2005; Swink *et al.*, 2006; Tyagi, 2006).

- *Use of the fuzzy theory to deal with uncertainty of incomplete information and imprecise human judgments* (Hsu *et al.*, 2003; Lin and Chen. 2004; Mohanty *et al.*, 2005; Xu *et al.*, 2007a; Huynh and Nakamori, 2009):

The fuzzy theory has been recognized as a powerful technique to tackle uncertainties. It has been widely used to cope with vague and subjective human judgments for better decision making.

- *Use of methods such as ranking, scoring, and weighing to prioritize and select new product ideas* (Henriksen and Traynor, 1999; Linton *et al.*, 2002; Coldrick *et al.*, 2005; Eilat *et al.*, 2008):

  These methods are straightforward and effective in facilitating decision making but are too simple to deal with complex problems. They are unable to take the correlations among criteria into consideration. Other approaches to support screening decision include the multi-attribute utility theory (Keeney and Raiffa, 1976), conjoint analysis (Green and Srinivasan, 1978), and analytic hierarchy process (AHP) (Saaty, 1980). Among these, AHP is frequently employed to address both the complex problems of prioritization and multi-attribute decision making (Zahedi, 1996; Calantone *et al.*, 1999; Ayag, 2005). Supported by some researchers, AHP has been an important approach to improve NPIS decisions (Rangaswany and Lilien, 1997; Calantone *et al.*, 1999).

The above-mentioned studies can overcome some difficulties in new product idea evaluation. However, they only provide limited support in making screening decisions. Advantages and drawbacks of major approaches to NPIS are summarized in Table 2.1. From Table 2.1, it is clear that current approaches have a common drawback. They can help managers prioritize all new product ideas based on performance and potential of success, and then select *only* a single new product idea, that is the best one among alternatives. However, when evaluating new product ideas concurrently, the current approaches are unable to determine which ideas should be chosen, especially if the ideas have similar probability of success. For example, a recent study (Huynh and Nakamori, 2009) proposed a fuzzy approach for new product screening to tackle experts' assessments in linguistic terms. The model concluded by providing a linguistic suggestion (i.e., non-preference, very little preference, little preference, moderate preference, much preference, very much preference, or most preference) as a guide for managers to make screening decisions. The linguistic suggestions are supportive only if managers have to select the best idea (the very best one idea) from the alternatives. However, it would still be difficult for managers if the new product ideas have similar linguistic suggestions such as much preference, moderate preference, and little preference. This probably confuses managers with which ideas are to be chosen and which discarded. This indicates that such approach is insufficient and impractical to use in screening decisions on all new product ideas. This drawback is not only described in this literature but is also common in other literature proposing approaches to NPIS (Calantone *et al.*, 1999; Lin and Chen, 2004; Kahraman *et al.*, 2007). Given this limitation, Module I: an idea screening decision model of the proposed iDSS is developed to overcome this drawback. It would be useful to determine the optimal value for making go or kill decisions on all ideas, thus assisting managers in evaluating the ideas concurrently and determining which ideas should be selected and killed.

Table 2.1 Advantages and drawbacks of major approaches to NPIS

Methods	Advantages	Drawbacks
Fuzzy decision making models, such as FAHP (Hsu *et al.*, 2003; Lin and Chen. 2004; Mohanty *et al.*, 2005; Xu *et al.*, 2007a; Huynh and Nakamori, 2009)	● Tackle the fuzziness of human judgments ● Can prioritize ideas and select the best project	● Involve complicated calculation ● When evaluating alternatives concurrently, this method is unable to determine which project(s) should be chosen, especially if projects have similar likelihood of success
Multi-attribute approaches, such as AHP (Rangaswany and Lilien, 1997; Calantone *et al.*, 1999)	● Useful in structuring complex multi-attribute decisions ● Rely on easily obtained managerial judgment data for idea evaluation ● Tackle the complex problem of prioritization that can prioritize ideas and select the best project	● Only rely on managerial inputs, which are subjective, on multiple criteria for evaluation ● When evaluating alternatives concurrently, this method is unable to determine which project(s) should be chosen, especially if projects have similar likelihood of success
Use of methods such as ranking, scoring, and weighing (Henriksen and Traynor, 1999; Linton *et al.*, 2002; Coldrick *et al.*, 2005; Eilat *et al.*, 2008)	● The most straightforward and effective method ● Can prioritize ideas and select the best project	● Too simple to deal with complex problems, such as fuzziness of human judgments ● When evaluating alternatives concurrently, this method is unable to determine which project(s) should be chosen, especially if projects have similar likelihood of success

2.3.3 Critical Criteria for Evaluating New Product Ideas

To develop Module I for NPIS in this research, it is necessary to account for the critical criteria for evaluating new product ideas. Previous research has shown that marketing and technical factors are important in new product idea evaluation (De-Brentani and Droge, 1988; Cooper, 1990b; Zirger and Maidique, 1990; Melissa, 2005; Swink *et al.*, 2006). In this decade, research emphasizing the consideration of risk or uncertainty in products' outcomes has been growing. The following evaluation criteria are found to be indispensable in new product idea evaluation, and they are strongly supported by the recent literature:

- Customer needs (Chin *et al.*, 2008);
- Market strength and attractiveness (De-Brentani and Droge, 1988; Lin and Chen, 2004);
- Technological or technical competency (De-Brentani and Droge, 1988; Calantone *et al.*, 1999; Lin and Chen, 2004);
- Manufacturability (Calantone *et al.*, 1999; Lin and Chen, 2004; Chin *et al.*, 2008);
- Logistics and distribution strength (De-Brentani and Droge, 1988; Calantone *et al.*, 1999; Lin and Chen, 2004; Chin *et al.*, 2008); and
- Risk or uncertainty in the project's outcome (Calantone *et al.*, 1999; Lin and Chen, 2004; Kahraman *et al.*, 2007; Chin *et al.*, 2008).

These criteria are thus chosen and included in this research to construct a new product idea assessment scorecard that is specific to resolve the NPIS problem. A scorecard is a critical and practical management tool for performance measurement (Phusavat *et al.*, 2009). Although a formal and systematic approach for evaluating new product ideas is beneficial to companies in making better screening decisions (De-Brentani and Droge, 1988), until now, an approach to facilitate go or kill decision making in a simple but effective manner has received little research attention from researchers. Designing a specific scorecard to help managers measure the performance of new product ideas is one of the necessities to address this problem. Module I of the proposed iDSS would achieve this. Furthermore, Module I also attempts to create a novel approach to NPIS decision making and hopefully filling the research gap by providing valuable insights for all managers involved in NPD.

2.4 Decision Support Systems for New Product Development

2.4.1 Current Decision Support Systems for New Product Development

At the front end of the NPD process, screening new product ideas is a preliminary decision-making practice. As mentioned before, there are often not only one but other decision gates in the NPD process. Once new product ideas are evaluated and chosen to be further developed in the next stage, companies still need to appraise and approve NPD projects to ensure which ones should be successful if launched. That is to gain return on investments by satisfying customer needs and capturing value from customers. Appraising NPD projects should often be more complicated than evaluating new product ideas. In view of this, using decision aids such as DSSs is often a practical solution to provide companies with useful information to understand a range of managerial aspects of a problem.

In recent years, many conventional and market-based DSSs for product design have been developed (Herrmann *et al.*, 2000; Harding *et al.*, 2001; Khoo *et al.*, 2002; Alexouda, 2005; Xu *et al.*, 2007a). They aid product classification (Mohanty and Bhasker, 2005), single product design (Balakrishnan and Jacob, 1995; Mohan *et al.*, 2007; Xu *et al.*, 2007a), product line design (Zha *et al.*, 2004; Alexouda, 2005; Kumar *et al.*, 2007), and market-based product development (Moskowitz and Kim, 1997; Herrmann *et al.*, 2000; Harding *et al.*, 2001; Chen *et al.*, 2002; Khoo *et al.*, 2002; Alexouda, 2005).

In this research, the DSSs for market-based product development have been discussed, because customer requirements are often aligned with new product success, and NPD and CRM issues are inseparable. Although some market-based DSSs for NPD found in the literature consider both design and marketing information (Moskowitz and Kim, 1997; Herrmann *et al.*, 2000; Harding *et al.*, 2001; Chen *et al.*, 2002; Khoo *et al.*, 2002; Alexouda, 2005), the influencing factors that they include vary widely.

2.4.2 Critical Factors for New Product Development

The existing studies highlight the key areas that ought to be considered in making decisions on NPD, including customer requirements, customer satisfaction, market demand, product quality, product design, and pricing. The following three areas, which cover various influencing factors, have been identified as significant and requisite in making NPD decisions. However, none of the currently available DSSs considers all of these areas concurrently.

- *Product attributes specified by designers* (Kahraman *et al.*, 2006; Xu *et al.*, 2007a):

  The product itself is the major stimulus that influences customer cognition and behavior. Customers may evaluate product attributes in terms of their own values, beliefs, and past experiences when they purchase (Solomon *et al.*, 2010). However, it is unlikely that customers will make a purchase based on product attributes alone. Their requirements and satisfaction are also vital, as is marketing competence.

- *Customer requirements and satisfaction* (Herrmann *et al.*, 2000; Melissa, 2005; Liu *et al.*, 2008):

  Capturing the voice of customers is essential in manufacturing products that have a high value for customers. Satisfying customer needs not only enables firms to build and retain customer relationships successfully, but also encourage positive word of mouth communication among customers, which in turn influence market demand.

- *Marketing competence* (De-Brentani and Droge, 1988; Lin and Chen, 2004)*:*

  Marketing activities usually serve as a catalyst to make customers recognize products and induce them to purchase. They also influence whether the purchase and use of a product is likely to be rewarding (Peter and Olson, 2008). Thus, high-quality marketing campaigns are likely to improve the market share gained from the introduction of new products. Conversely, poor marketing planning and execution have been blamed for the failure of new products (Cooper, 1978).

2.4.3 Decisive Factor for New Product Development Decision Making

In contemporary literature, most current DSSs help managers select the best new product among alternatives in terms of market share, return maximization, or minimization of development time (Matsatsinis and Siskos, 1999; Wassenaar and Chen, 2001; Alexouda, 2005; Lawson *et al.*, 2006; Kahraman *et al.*, 2007; Hung *et al.*, 2008). For example, Hung *et al.* (2008) developed an integrated information system to select alternatives of product design based on time and cost required in the development cycle. Kahraman *et al.* (2007) proposed a decision-making approach for the selection of new products based on the return maximization (in terms of profit, strategic impact, and efficiency of the development process) of a product. However, the measurement of market share or return maximization excludes the time value of money, whereas that of minimization of development time disregards market demand and the effect on customer behavior. These shortcomings may affect the outcome of NPD. As discussed previously, the value process, customer satisfaction, and customer relationships are prerequisite for the success of NPD, which results in business growth. Excluding experts' judgments, NPD decisions should be made according to the behavior and perspective of customers, as stated earlier. Customers' involvement in NPD decision making is essential.

The shortcomings of existing systems can be overcome by modeling customer purchasing behavior in a way that takes into account the impacts of all of the important areas discussed, and by calculating the value of customers to a company (i.e., net customer lifetime value (NCLV) in this research) to aid the selection of the best new product to launch. This research attempts to build Module III: a dynamic decision model of the proposed iDSS for NPD that performs these tasks. It helps managers understand the managerial aspects of the product decision problems and make appropriate decisions on market-based NPD.

Customer lifetime value (CLV) is an example that illustrates the value of a customer to a company, which is the value outcome derived from creating and delivering superior customer value (Payne and Holt, 2001). As far as the company is concerned, CLV is the net present values of all future profit or loss obtained from a customer during his/her entire purchasing lifetime with a company (Berger and Nasr, 1998). CLV plays a significant and important role in CRM modeling according to Chen *et al.* (2004b) and Ip *et al.* (2006). Since not all customers are equally profitable, it is useful for a company to differentiate the most profitable customers from the least; CLV is a powerful tool in classifying customers. Resources can then be allocated and an appropriate business strategy formulated for business growth (Kumar and Reinartz, 2006). Researchers have adopted CLV models to analyze how the marketing actions of a company affect customer behavior, including acquisition, retention, and expansion. The results would be used to estimate the purchase profitability and CLV of a customer to a company (Kumar and Reinartz, 2006). Approaches of modeling and estimating CLV differ from one researcher to another. These approaches include building an individual customer level of CLV model (Venkatesan and Kumar, 2004), proposing a segment level of CLV model (Rosset *et al.*, 2003), building separate models for customer acquisition and retention (Reinartz and Kumar, 2005), and building a model for recency and frequency with a separate model for monetary value (Fader *et al.*, 2005).

In the literature, calculating the transactions followed by making NPD decisions based on profit maximization is the common practice as discussed before. From the managerial perspective, calculating CLV is a more accurate way than the transaction-based calculations to estimate the value gained by a company. This is because CLV takes the time value of money and relationship between a customer and a company into account. As stressed by Berger and Nasr (1998), the literature on the topic of CLV is vast; most of which has considered CLV a decision making criterion and an alternative to profitability. It is perceived that calculating CLV is a more suitable and accurate way to be a decision making criterion for the selection of new products than the transaction-based calculations and profit maximization. To estimate the value of customers, NCLV is exploited in this research. It is transformed from CLV and serves as a decisive factor for NPD decisions. This research is not centered on differentiating the most profitable customers from the least, but analyzing the profitability of a NPD project through considering customer purchasing behavior and their relationships with a company. Hence, NCLV, instead of CLV, is formulated and applied here.

The mathematics of CLV is given here while the formulation of NCLV is presented in a later chapter (see Chapter 5). Assuming that all cash flows take place at the end of a time period, the fundamental equation used for calculating CLV is described as follows:

$$CLV = \sum_{t=1}^{T} \frac{R_t}{(1+d)^t} - \sum_{t=1}^{T} \frac{C_t}{(1+d)^t} = \sum_{t=1}^{T} \frac{R_t - C_t}{(1+d)^t} \qquad (2.1)$$

where R_t is the revenue gained from customers at time t; C_t is the total cost of serving the customers in the marketing function at time t; t is the period of cash flow, $t = 1,2, \dots, T$; and d is the discount rate.

2.5 Decision-making Tools and Techniques

2.5.1 Multi-attribute Decision-making Techniques

In the NPD and CRM domains, experts' judgments and customer buying decisions on new products are often based on a comparative evaluation of the characteristics of various products. Characteristics include, but not limited to, product performance, quality, design, price, time to market, and brand. Thus, assessing new product characteristics is, in essence, a multi-attribute decision problem. As stated before, customers' involvement in NPD is crucial. Apart from experts' judgments, companies should listen to the voice of customers, followed by developing new products according to customers' actual needs. Prioritizing product characteristics from the customers' perspective is also viewed as a multi-attribute decision problem, and it is investigated in this research with the support of multi-attribute decision-making techniques.

Multi-attribute decision making is crucial to precisely evaluate data, as human assessments are often fuzzy and subjective. The investigation of different decision-making methods is an interesting research area, and various approaches have been proposed over the past decade. The weighted sum method is well known and has been widely used, particularly in single-dimension problems (Fishburn, 1967). Multi-attribute utility theory (Keeney and Raiffa, 1976), AHP (Saaty, 1980), and conjoint analysis (Green and Srinivasan, 1978) are commonly applied in the literature to address multi-attribute decision problems. Among these, AHP is relatively popular due to its ability to cope with complex multi-dimensional decision-making problems in a simple manner. Apart from AHP, quality function deployment (QFD) is another popular method to hear the voice of customers. However, it is mainly used to transform customer requirements into engineering characteristics, and then to set target values for product design and manufacturing, according to the literature (Akao, 1990; Chan and Wu, 2002). This research focuses on precisely recognizing customers' actual needs, instead of setting the target values for product design and manufacturing, QFD is therefore not adopted. In addition, the voice of customers is usually vague and imprecise and QFD is likely to be incapable of dealing with such issue.

The uncertainty and fuzziness that result from unreliable and unavailable information, information vagueness, human assessments, and so on often influence the outcome of the final decisions. The fuzzy theory firstly proposed by Zadeh (1975) aims to solve such problems and the activities, and observations of the problems are described imprecisely, vaguely, and uncertainly. The term "fuzzy" refers to the situation, in which there are no well-defined or crisp boundaries that can be applied to describe these activities and observations (Chen and Hwang, 1991). The fuzzy theory plays an important role in dealing with the ambiguities in a system (Zimmermann, 1996), and has been applied to a variety of decision models. The application of fuzzy approaches to handle the uncertainties inherent in multi-dimensional decision-making problems is of great interest in managerial decision-making models (Lai and Hwang, 1994; Liang and Wang, 1994; Gogus and Boucher, 1997). The fuzzy theory, which converts linguistic variables into fuzzy numbers under ambiguous assessments, has been found to resemble human reasoning and thus support decision making (Zadeh, 1975).

The AHP is suitable for handling multi-dimensional problems that involve subjective judgments; however, it may not fully reflect human thinking patterns and assessments, which are linguistics-based and vague. The fuzzy analytic hierarchy process (FAHP), in contrast, is combined by the fuzzy theory and AHP to provide a more accurate description of the decision-making process (Cheng, 1999; Huang *et al.*, 2008), and fuzzy pairwise comparison is more rational than crisp comparison in representing uncertain judgments (Entani *et al.*, 2001).

There are numerous applications of the fuzzy theory for solving multi-attribute decision-making problems. Perrone (1994) employed a fuzzy multi-attribute decision model to evaluate advanced manufacturing systems, and Coffin and Taylor (1996) applied fuzzy logic to multi-attribute R&D project selection. Chan *et al.* (2000) and Hsu *et al.* (2003) made use of the fuzzy multi-attribute method to evaluate and select technology projects, whereas Buyukozkan *et al.* (2007) presented a fuzzy group decision-making approach to analyze multiple preferences in product development. Xu *et al.* (2007a) employed the fuzzy theory to evaluate product design alternatives based on functionality, reliability, and manufacturability, and Lin and Chen (2004) developed a fuzzy logic-based screening model to cope with the ambiguity and complexity in product screening decisions. Gustafsson and Gustafsson (1994) used the conjoint analysis to determine the importance of customer requirements, and Kwong and Bai (2002) used FAHP to determine the importance weights of customer requirements in QFD. Other studies that make use of FAHP can be found in the literature (Buckley, 1985; Cheng and Mon, 1994; Chen, 2000; Csutora and Buckley, 2001; Mikhailov, 2003; Lau *et al.*, 2006).

FAHP, being a combination of AHP and the fuzzy theory, is a powerful and systematic approach for solving multi-attribute decision-making problems. It is regarded as the most appropriate and effective way to solve the decision-making problems in NPD. As a result it is employed in this research. FAHP used herein is on the basis of FAHP proposed by Kwong and Bai (2002) with an addition of an extra formula. The formula will be described in Chapter 3. FAHP is employed in Module II: a customer perception model of the proposed iDSS. This is to investigate customers' judgments on the relative importance of the product characteristics and on whether the customers decide to buy a product or not.

2.5.2 Markov Analysis

Markov analysis is one of the mathematical techniques for sequential decision making under uncertain circumstances. It deals with the probabilities of future occurrences by analyzing presently known probabilities (Render *et al.*, 2006). Markov analysis makes use of the transition probabilities matrix, known as the Markov process, to illustrate the likelihood that the system will change from one period to the next, and to predict future states or conditions. Markov analysis is famous for its flexibility and sophistication in decision making (Isaacson and Madsen, 1976; Puterman, 1994).

Traditional Markov Model

In the traditional Markov model, the Markov chain equation with a state space $s = \{1,2,\dots,S\}$ can generally be expressed as follows:

$$p_{ij} = P(X_{t+1} = j|X_t = i) \tag{2.2}$$

where p_{ij} is the probability of switching to state j from state i at time t; i and j are states in s; X is a random event or variable in the process; $0 \leq p_{ij} \leq 1$; and $\sum_{j=1}^{S} p_{ij} = 1$. A transition probabilities matrix can then be formulated below.

$$P^t = \begin{bmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,S-1} & p_{1,S} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,S-1} & p_{2,S} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ p_{S-1,1} & p_{S-1,2} & \cdots & p_{S-1,S-1} & p_{S-1,S} \\ p_{S,1} & p_{S,2} & \cdots & p_{S,S-1} & p_{S,S} \end{bmatrix}$$

Supported by many studies, the Markov model is found to be commonly applied for solving decision problems, including predicting the patterns in the enrollment of a medical program among particular patients and its related funding requirements (Bartnyska, 1995), modeling customer relationships (Pfeifer and Carraway, 2000), modeling the travel patterns of individuals (Janssens *et al.*, 2005), estimating e-customer lifetime value (Paauwe *et al.*, 2007), estimating the churn probability for customer targeting and marketing actions (Burez and Van-den-Poel, 2007), determining the optimal termination time of TV shows (Givon and Grosfeld-Nir, 2008), and evaluating manufacturing system performance (Dasci and Karakul, 2008). There is an increase in demand for research on marketing and customer behavior using the Markov model. This reveals that it is increasingly important to evaluate customer relationships and to support business decisions, which both make for business growth in this highly competitive market. Most of these models, however, are developed from the perspective of the marketing function only. Few studies have considered the impacts of product-related and customer-related factors on customer purchasing behavior in a Markov model.

Markov analysis, when applied to CRM, is a probabilistic model accounting for the uncertainties in customer relationships. In addition, the Markov model uses information obtained from a customer relationship, such as probability and expected value to measure future relationships, instead of just calculating the average profits from all customers. It has been claimed that the major advantages of the Markov model are its flexibility and sophistication (Isaacson and Madsen, 1976; Puterman, 1994). To study customer relationships and estimate the value of customers to a company, the Markov model is used. It is appropriate to model customers' acquisition and retention which are influenced by the factors related to customers, marketing, and products. After this modeling, NCLV can be calculated. This is applied to Module III of the proposed iDSS.

Hidden Markov Model

Unlike the traditional Markov model, hidden Markov model (HMM) contains a finite number of states which are unobserved (hidden). The typical HMM consists of the following characteristics (Rabiner, 1989).

- $S = \{s_1, s_2, s_3, \cdots, s_N\}$: The (hidden) states in the model, where N is the number of hidden states.
- $V = \{v_1, v_2, v_3, \cdots, v_M\}$: The observation states in the model, where M is the number of distinct observation symbols in a state.
- $O = \{o_1, o_2, o_3, \cdots, o_T\}$: The observation sequence, where T is the length of observation sequence.
- $X = \{x_1, x_2, x_3, \cdots, x_T\}$: The (hidden) state sequence.
- $A = \{a_{ij}\}$: The state transition matrix, in which $a_{ij} = P(x_t = s_j | x_{t-1} = s_i)$

represents the state transition probability from s_i to s_j at time t, where $1 \leq i, j \leq N$, $1 \leq t \leq T$, and $x_t \in \{s_1, s_2, s_3, \cdots, s_N\}$.

- $B = \{b_j(k)\}$: The observation symbol matrix, in which $b_j(k) = P(o_t = v_k | x_t = s_j)$ denotes the observation symbol probability of generating a v_k at s_j at time t, where $1 \leq k \leq M$ and $o_t \in \{v_1, v_2, v_3, \cdots, v_M\}$.
- $\Pi = \{\pi_i\}$: The initial state distribution, where $\pi_i = P(x_1 = s_i)$ represents the probability of being in s_i at time t=1.

In addition, a_{ij}, $b_i(k)$, and π_i possess properties of $\sum_{j=1}^{N} a_{ij} = \sum_{k=1}^{M} b_i(k) = \sum_{i=1}^{N} \pi_i = 1$ and $a_{ij}, b_j(k), \pi_i \geq 0$. Given a fixed X and O, a discrete HMM is formally denoted as $\lambda = (A, B, \Pi)$, which indicates the parameter set. In HMM, the current state is dependent on only the previous state, $P(x_t | x_1^{t-1}) = P(x_t | x_{t-1})$, that is the Markov assumption. The current output observation is independent of the previous observations but dependent only on the current state.

HMM is a powerful stochastic and statistical technique and is strongly capable of explaining the occurrence of observations. It is also useful in solving decision problems involving risks over time, repetitive events, or time dependence (Sonnenberg and Beck, 1993). HMM has the advantage of handling new data robustly, is computationally efficient to develop and evaluate, and is well suited to the natural language domain (Seymore *et al.*, 1999; Li *et al.*, 2005). It can be used to establish an effective approach to resolve NPIS decision problems. It can also classify new product ideas for NPIS decisions through recognition of their evaluation performance and prediction of their probabilities to succeed.

HMM's popularity has been growing, and it has been successfully applied in a wide variety of fields owing to its strong mathematical framework and theoretical foundation. Furthermore, it has particularly served as a predictor or classifier for speech recognition (Rabiner, 1989), DNA and protein sequence analysis (Hughey and Krogh, 1996), information extraction (Freitag and McCallum, 1999; Seymore *et al.*, 1999), behavior analysis (Jebara and Pentland, 1999), information retrieval (Miller *et al.*, 1999), rainfall occurrence (Srikanthan and Mcmahon, 2001; Robertson *et al.*, 2003), stock market forecasting (Hassan and Nath, 2005), text classification (Yi and Beheshti, 2009), and so on. Clearly, HMM is a powerful tool for various applications. Although its application to NPD is hardly found, the stochastic and statistical properties of HMM is suitable for addressing the issue of NPIS.

As discussed previously, it is important to develop an effective algorithm for computing the evaluation parameters of new product idea and facilitating NPIS decision making. It is necessary to rank new product ideas and determine the optimal value for distinguishing the successful new product ideas from the inferior ones, so that a go or kill decision can be made. Due to the convincing mathematical framework of HMM, it is suitable to be developed as a simple but effective algorithm to solve the NPIS decision-making problems in this research. Module I: an idea screening decision model for NPIS is thus created in the proposed iDSS to support go or kill decision making.

2.5.3 System Dynamics

System dynamics, which is related to systems thinking, is defined as the principle and technique of feedback control systems for modeling, analyzing, and understanding the dynamic behavior of complex systems (Tarek and Stuart, 1991). System dynamics, along with system modeling and computer-based simulation, is an interactive tool. It is a valuable aid for better understanding of the dynamic behavior, policy design, and decision making in the complex feedback systems (Wolstenholme, 1990; Tarek and Stuart, 1991; Lin *et al.*, 1998; Vandal, 2003). System dynamics has dramatically extended into several disciplines, such as strategic planning (Georgantzas, 1996; Lyneis, 2000; Lam *et al.*, 2010), business process reengineering (Georgantzas, 1996), project management (Rodrigues and Bowers, 1996a; 1996b), policy design and analysis (Richardson, 1991; Saysel *et al.*, 2002; Lai *et al.*, 2003), business decision making (Angerhofer and Angelides, 2000; Chan and Ip, 2008; Ip *et al.*, 2008; Chan *et al.*, 2010), supply chain management (Lai *et al.*, 2003), investment decisions (Marquez and Blanchar, 2006), and so forth.

The flexibility of system dynamics brings systems thinking into a rigorous and testable manner (Wolstenholme, 2005). Companies can simply make use of system dynamics tools for effective system modeling and simulation. The methodology often involves five steps:

1. Defining a specific issue or problem of the system to be examined;
2. Developing a dynamic hypothesis to explain the cause of the problem;
3. Building a model to simulate the root of the problem;
4. Testing and refining the model based on its dynamic behavioral patterns in terms of effectiveness and efficiency; and
5. Implementing an appropriate solution to alleviate the problem.

The key contributions of system dynamics model are the stock-flow map and the simulation model. The main building blocks of system dynamics model are "stock" and "flow," which represent the accumulation and movement (inflow and outflow) of resources, including information and materials in the system, respectively. In addition, "connector" links model elements together for transmission of resources, and "converter" converts inputs into outputs. The model helps illustrate the interrelationship of system behavior and resource flow. The stock-flow diagram (see Figure 2.3) constructed can then be used for simulation.

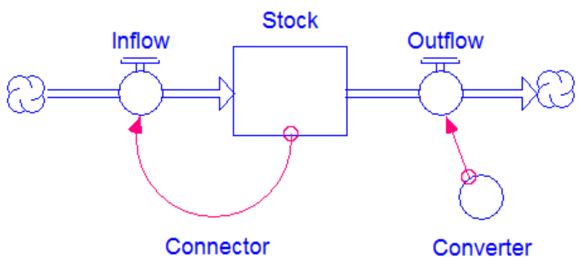


Figure 2.3 System dynamics model

System dynamics is regarded as a strategic and planning tool. Forrester (1968) and Wolstenholme (1990) pointed out that most of the problem-solving models cannot give rise to a systematic and profound analysis of complex systems, such as spreadsheets, data analysis, and process mapping. In addition, Rodrigues and Bowers (1996a) stated that traditional planning techniques such as the Program Evaluation and Review Technique, as well as the Critical Path Method cannot support experimentation for policy establishment. However, system dynamics is a more comprehensive and sophisticated approach with qualitative modeling and quantitative simulation capabilities, enabling experimentation which achieves more reliable and robust outcomes as well as establishes appropriate policies (Chritamara *et al.*, 2002). System dynamics can serve as an analytical tool for strategic decision making through simulation, and as a planning tool for systems thinking through model construction. This explains why system dynamics becomes more valuable and popular in the field of strategic management. However, in the field of NPD, there is a minority of literature and studies examining the interrelationship of NPD, customer requirements, and satisfaction with a system dynamics approach.

System dynamics is a valuable and sophisticated approach that companies can utilize visual representation to model the system for better illustration, and to simulate the model with different scenarios over time for better understanding of the dynamic behavioral patterns. Indeed, companies can make use of the practical and realistic system dynamics model to make more explicit assumptions strategically, and they can shape their understanding, policies, and decisions regarding the system toward its perfection and success. Based on the simulation results, companies would often craft strategies and policies consistently, as well as redesign the business and NPD processes or systems for achieving their business objectives. By using system dynamics, companies can enhance their insights into the problems or system structure with better understanding of the complexity and of the dynamics caused by different influencing elements. Thus, system dynamics as a strategy comes to the top management concerns (Helms, 1990). System dynamics, making use of a set of qualitative and quantitative tools based on realistic hypotheses and a broad range of data (Sterman, 2000), is ideal for extensive experimentation that even laymen or practitioners can easily master it. System dynamics is regarded as a useful and appropriate technique for constructing Module III: a dynamic decision model of the proposed iDSS in this research.

2.6 Chapter Summary

This chapter has shown the strong correlation between NPD and CRM. The focus of CRM in this research is the value process, customer satisfaction, and customer relationships. The literature review also reveals that decision making in NPD should not only focus on product attractiveness to customers but also both customer and marketing considerations. This provides grounds for conducting this research by assimilating NPD and CRM for successful NPD. Literature related to NPD has been reviewed and covered in this chapter, including the importance of NPD, the NPD process, NPIS, and DSSs for NPD. Such discussion explains the needs of the proposed iDSS. Various decision-making tools and techniques that are applied in this research have also been described in this chapter.

From the literature, key factors that have been stressed and included in existing DSSs for the sake of NPD are listed in

Table 2.2. This highlights the insufficiency of the current practices when making NPD decisions. From

Table 2.2, it is common to take customer-related factors and product attributes into account. Marketing-related factors (such as word of mouth, marketing competence, and market strength), internal factors (such as technical competency, manufacturability, and distribution channels), and other factors are however seldom considered. There are very limited studies taking all these key factors shown in

Table 2.2 into consideration when making decisions in NPD, except the current research. This again underlines the originality and value of the proposed iDSS.

The purposes of the existing studies and methods used in them about decision making in NPD are summarized in Table 2.3. These studies mainly serve one of these three purposes – evaluating new product ideas and projects for selection, tackling the product design problems, and improving effectiveness and quality of the decision making process. Table 2.3 reveals that the number of studies to evaluate new product ideas and projects for selection is relatively low. This research therefore attempts to enrich the literature by developing the proposed iDSS, which is capable of evaluating new product ideas and projects. Multiple methods, including Markov analysis, the multi-attribute decision-making technique, the scorecard technique, the fuzzy theory, and system dynamics, are applied in this research to tackle the problems stated in Chapter 1 so as to make up for the deficiency of using only one particular method. Furthermore, the integration of the multiple methods used for the development of the proposed iDSS is novel to the literature.

Table 2.2 Key factors considered in NPD decision making

Studies on NPD Decisions \ Key Factors Included	Product attributes	Technical competency	Manufacturability	Logistics strength/Distribution channels	Risk/uncertainty	Marketing competence/effectiveness	Word of mouth	Market strength/attractiveness	Customer needs/requirements	Relative importance of customer needs	Customer satisfaction	Customer behavior	Financial return
Balakrishnan and Jacob (1995)	✓									✓			
Moskowitz and Kim (1997)	✓								✓	✓	✓		
Calantone *et al.* (1999)	✓		✓	✓	✓	✓			✓				
Matsatsinis and Siskos (1999)		✓						✓	✓				✓
Herrmann *et al.* (2000)	✓								✓	✓	✓		
Harding *et al.* (2001)	✓								✓	✓			
Wassenaar and Chen (2001)	✓								✓				✓
Khoo *et al.* (2002)	✓												
Lin and Chen (2004)	✓	✓	✓	✓	✓			✓					
Alexouda (2005)	✓							✓					✓
Lawson *et al.* (2006)		✓			✓			✓					✓
Marquez and Blanchar (2006)	✓									✓		✓	✓
Buyukozkan *et al.* (2007)	✓								✓				
Fung *et al.* (2007)	✓	✓							✓	✓			
Kahraman *et al.* (2007)	✓				✓								✓
Xu *et al.* (2007a)	✓		✓					✓					
Chin *et al.* (2008)	✓		✓	✓	✓	✓			✓				
Hung *et al.* (2008)	✓								✓				
Liao *et al.* (2008)	✓	✓						✓	✓				
Liu *et al.* (2008)	✓								✓	✓			
The proposed iDSS	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 2.3 Studies on decision making in NPD

	Evaluate new product ideas or projects for selection	Determine product specifications or provide solutions for product design problems	Improve effectiveness and quality of the decision making process	Method(s) used
Balakrishnan and Jacob (1995)		✓		● Dynamic programming ● Genetic algorithm
Moskowitz and Kim (1997)		✓		● Quality function deployment
Calantone *et al.* (1999)	✓			● Analytic hierarchy process
Matsatsinis and Siskos (1999)			✓	● Statistical analysis ● Consumer choice model
Haque *et al.* (2000)			✓	● Case based reasoning
Herrmann *et al.* (2000)		✓		● Quality function deployment ● Means-end analysis
Harding *et al.* (2001)		✓		● Quality function deployment ● Fuzzy theory
Kengpol and O'Brien (2001)			✓	● Analytic hierarchy process ● Statistical analysis
Wassenaar and Chen (2001)				● Statistical analysis
Khoo *et al.* (2002)			✓	● Analytic hierarchy process
Linton *et al.* (2002)	✓			● Data envelopment analysis
Buyukozkan and Feyzioglu (2004)			✓	● Fuzzy theory ● Multi-attribute decision-making technique
Lin and Chen (2004)	✓			● Fuzzy theory

(To be continued on the next page)

Table 2.3 Studies on decision making in NPD

	Evaluate new product ideas or projects for selection	Determine product specifications or provide solutions for product design problems	Improve effectiveness and quality of the decision making process	Method(s) used
Alexouda (2005)		✓		● Evolutionary algorithm
Lawson *et al.* (2006)	✓			● Scoring technique ● Cost benefit analysis
Lo *et al.* (2006)	✓			● Fuzzy theory
Marquez and Blanchar (2006)	✓			● Dynamic programming
Buyukozkan *et al.* (2007)		✓		● Fuzzy theory ● Quality function deployment
Fung *et al.* (2007)		✓		● Quality function deployment ● Matrix analysis ● Multi-attribute decision-making technique ● Possibilistic optimization
Kahraman *et al.* (2007)	✓			● Fuzzy theory ● Multi-attribute utility method ● TOPSIS method
Xu *et al.* (2007a)			✓	● Fuzzy theory
Chin *et al.* (2008)	✓			● Evidential reasoning approach ● Analytic hierarchy process

(To be continued on the next page)

Table 2.3 Studies on decision making in NPD

	Evaluate new product ideas or projects for selection	Determine product specifications or provide solutions for product design problems	Improve effectiveness and quality of the decision making process	Method(s) used
Hung *et al.* (2008)		✓		● Quality function deployment ● Design structure matrix
Liao *et al.* (2008)		✓		● Data mining
Liu *et al.* (2008)		✓		● Preference modeling ● Utility analysis ● House of quality
Hu and Bidanda (2009)			✓	● Markov analysis ● Dynamic programming
Zhai *et al.* (2009)		✓		● Multi-attribute decision-making technique ● Grey relation analysis
The proposed iDSS	✓			● Markov analysis ● Multi-attribute decision-making technique ● Scorecard technique ● Fuzzy theory ● System dynamics

CHAPTER 3 AN IDEA SCREENING DECISION MODEL FOR NEW PRODUCT IDEA SELECTION

3.1 Introduction

The previous chapter discussed the extant literature on new product development (NPD), customer relationship management (CRM), and various decision-making tools and techniques. With the support of such discussion, Module I: an idea screening decision model of the proposed iDSS is introduced in this chapter. Module I is to perform an initial, yet important, evaluation of new product ideas at the front end of the NPD process. The theoretical framework and development of Module I are described. The application and validation of Module I are then illustrated and discussed in detail through a case study.

Module I is a novel strategic approach for new product idea screening (NPIS) decisions and it combines an evaluation scorecard and a hidden Markov model (HMM). A scorecard is constructed to evaluate new product ideas on several criteria, including customer needs, market strength, technical competency, manufacturability, as well as logistics and distribution strength. With a consideration of a risk factor, namely risk buy, an HMM is then developed accordingly to predict the overall performance of new product ideas in terms of success probability. To apply and validate Module I, it is trained and tested through a case study by using the historical data of the case company, which is a world-class leading company in the power tool industry as described previously.

3.2 Theoretical Framework and Development of the Idea Screening Decision Model

NPIS, at the front end of the NPD process, plays a crucial role in the NPD practice. Performing an initial NPIS eliminates potentially inferior and worthless new product ideas before development, production, and commercialization, and this can prevent companies from investing unrecoverable money, time, and resources. Therefore, there is a great necessity to eliminate inferior new product ideas as early as possible at the front end of the NPD process before considerable investment is to be made. At this early NPD stage, companies should evaluate which new product ideas are worthy of further investment in terms of the expected market response and the internal proficiency in developing such ideas. In order to make such NPIS decisions, predicting the success probability of new product ideas is necessary. Module I: an idea screening decision model is developed to perform these tasks.

Figure 3.1 shows the framework of Module I, which is to support NPIS decision making, as well as its data process in practice. As NPD experts often make linguistic judgments on new product ideas based on the business environment, market opportunity, company's competency and resources, and corporate strategies, this information is needed to support the subsequent development of Module I. To develop Module I, an evaluation scorecard and an HMM are formulated. The evaluation scorecard actually guides experts through the evaluation process. It translates their linguistic judgments into ratings according to several criteria. The ratings on each criterion are aggregated and then normalized. The outputs of the evaluation scorecard serve as the inputs of the HMM. The success probability of each new product idea is eventually determined through this module. Using computer applications such as Excel and Matlab is helpful in the development of Module I. The details of the development of the evaluation scorecard and the HMM are explained afterward.

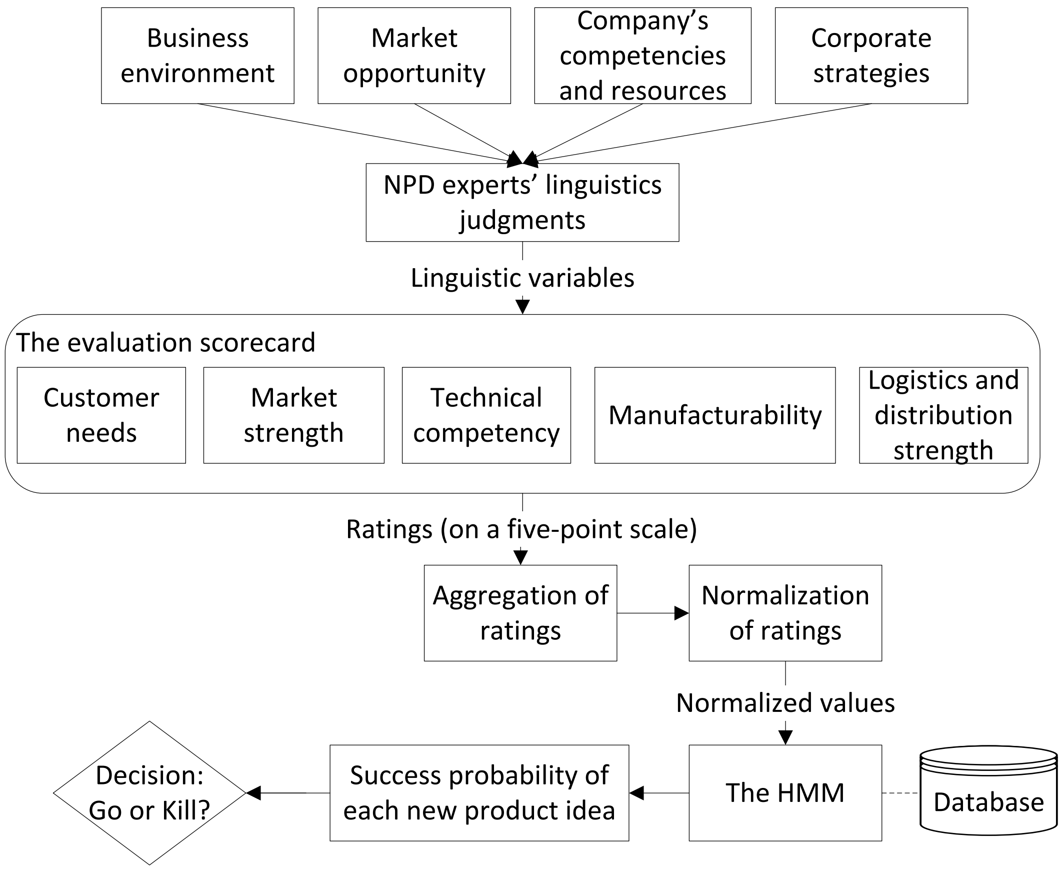


Figure 3.1 Framework of the idea screening decision model

3.2.1 Evaluation Scorecard for Assessing New Product Ideas

With reference to the literature discussed previously, a scorecard is a critical and practical management tool for performance measurement (Phusavat *et al.*, 2009). The scorecard technique is flexible and effective. To evaluate the performance of new product ideas and quantify linguistic judgments for measurement, the scorecard technique is suitable and thus applied to measure the performance of new product ideas. Constructing a specific evaluation scorecard for the assessment of new product ideas constitutes the first part of Module I. This scorecard is designed to help companies evaluate new product ideas based on multiple criteria and to translate linguistic terms into quantifiable and comparable variables. The steps to design and construct the evaluation scorecard are demonstrated in Figure 3.2 and are described below:

1. To identify and select a set of evaluation criteria for NPIS decision making;
2. To define the linguistic terms which are used to describe the criteria selected; and
3. To translate the linguistic terms into performance ratings based on a five-point scale in order to establish the scorecard.

As discussed in Chapter 2, six criteria are indispensable in the evaluation of new product ideas. These criteria include customer needs (CN), market strength (MS), technical competency (TC), manufacturability (MANU), logistics and distribution strength (LDS), and risk of investing in the ideas (which is named as risk buy (RB) in this research). They are supported by the literature (De-Brentani and Droge, 1988; Calantone *et al.*, 1999; Lin and Chen, 2004; Kahraman *et al.*, 2007; Chin *et al.*, 2008) mentioned previously. They are thus chosen and included in this research to construct Module I, which is specifically designed to resolve the NPIS problem. Terminology of the six criteria is explained in Table 3.1. The five criteria (including, CN, MS, TC, MANU, and LDS) are used in the formulation of the evaluation scorecard while RB is included in the HMM, which is introduced later. Besides, the performance of new product ideas is measured in a five-point scale, which is a common and popular scale used in performance evaluation (Lesjak and Vehovar, 2005; Laitinen, 2009). In fact, the use of a three-point scale is too simple, and it is insufficient to reflect experts' opinions on new product ideas, while the use of a seven-point or nine-point scale may make the evaluation ratings imprecise because the ratings would be too spread-out, causing the data to be futile and useless. The evaluation scorecard developed is illustrated in Table 3.2.

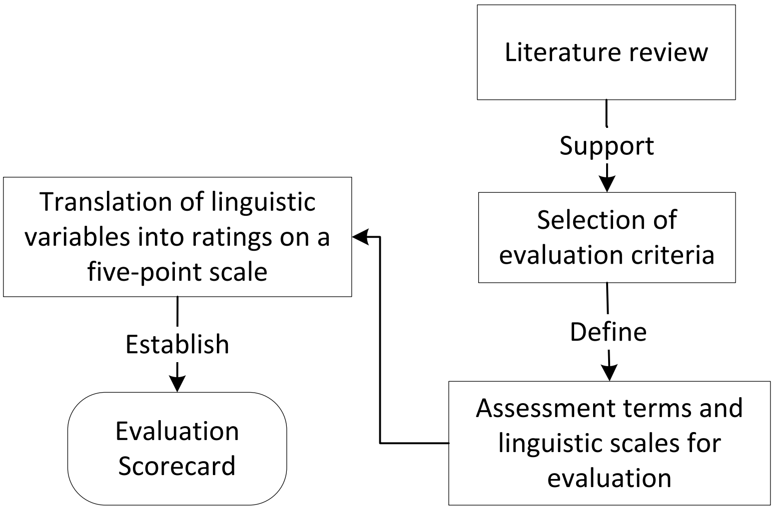


Figure 3.2 Framework of the evaluation scorecard

Table 3.1 Terminology of the six criteria used in Module I

Terms	**Implications**
Customer Needs (CN)	Fulfillment of customers' and the target segment's needs through the new products
Market Strength (MS)	The market potential of the new products in terms of high expected sales growth and profit potential
Technical Competency (TC)	The competency that the company possesses in designing and developing the new product ideas vis-à-vis the quality expected by customers, such as technical know-how, skills, and experiences
Manufacturability (MANU)	The availability, flexibility, and capacity of the manufacturing technology and process
Logistics and Distribution Strength (LDS)	The accessibility of the logistics and distribution channels
Risk Buy (RB)	Investments of the company in developing the new product ideas despite uncertainties (such as changes in customer needs and market demand, manufacturing malfunction, and deficient competency)

Table 3.2 Evaluation scorecard for assessing new product ideas

Score	**Market Factor**		**Technical Factor**
	Customer needs (CN)	Market strength (MS)	Technical competency (TC)
5	Customer needs are immediately met, and contractual commitments to buy products are already present.	A highly growing market: customers lead the market sector.	Our core competency, we are experts on this as we have done this before.
4	Customer needs are met, which are also identified.	Emerging market: customers are recognized as active for the product.	Our core competency but we have not done a project like this before
3	Market needs are evident.	Mature market	Not new-to-the-firm but not one of our core competency
2	Extensive market development is needed.	Declining market	New-to-the-firm but not new-to-the-industry
1	No apparent need for the product is found.	Unknown	New-to-the-world

(To be continued on the next page)

Table 3.2 Evaluation scorecard for assessing new product ideas

Score	**Factor of Time to Completion** Manufacturability (MANU)	Logistics and distribution strength (LDS)
5	Current manufacturing capabilities are qualified (we have done it before), and capacity exists.	Current channels are already appropriate.
4	Minor modifications to the current manufacturing technology/process are needed, and these changes are known.	A combination/modification of current channels is required.
3	Significant changes in the current manufacturing technology/process are needed, and these changes are known. Alternatively, external manufacturing capability exists and provides support.	New channels are required but current channels can serve as a foundation.
2	The manufacturing technology/process is new-to-the-firm but not new-to-the-industry.	New-to-the-firm channels are required.
1	The manufacturing technology/process is unknown to the world.	New-to-the-world channels are required.

3.2.2 Hidden Markov Model

After constructing the evaluation scorecard, the HMM, which is linked to the scorecard, is developed to predict the success probability of new product ideas through analyzing the results obtained from the scorecard. The development of the HMM is based on its theory discussed in Chapter 2. Designing the HMM is challenging but vitally important as it serves as the foundation of Module I. The framework of the HMM developed in this research is shown in Figure 3.3. Three phases have to be carried out in general, namely (a) phase 1: the design of HMM, (b) phase 2: the development of HMM, and (c) phase 3: the validation of HMM. They are described as follows:

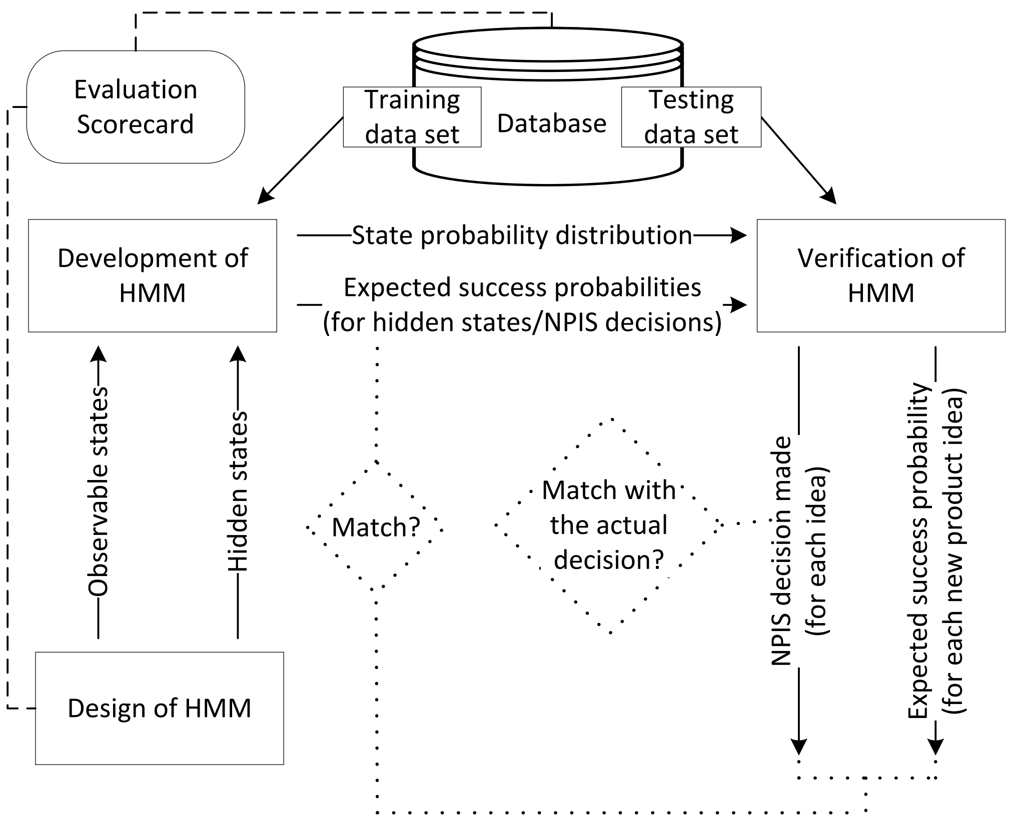


Figure 3.3 Framework of the HMM

Phase 1: The number of hidden and observable states has to be identified, and their representations have to be defined. In this research, a discrete HMM with two hidden states ($n = 2$) and six observable states ($m = 6$) is taken into account. This is because either a go or kill decision can be made during NPIS, forming the two hidden states: $S = \{s_1, s_2\} = \{Go, Kill\}$. Moreover, such decisions are made through evaluating new product ideas using the six criteria mentioned previously. The six observable states, $V = \{v_1, v_2, v_3, v_4, v_5, v_6\} = \{CN, MS, TC, MANU, LDS, RB\}$, are thus defined in the HMM. With two hidden states and six observable states, the state transition probability distribution of the hidden states (see Equation 3.1) and the observation symbol probability distribution of the observable states (see Equation 3.2) are as follows:

$$A = (a_1, \cdots, a_m) = (a_1, a_2) = (a, 1 - a) \tag{3.1}$$

$$B = \begin{pmatrix} b_{i1} & \cdots & b_{in} \\ \vdots & \ddots & \vdots \\ b_{m1} & \cdots & b_{mn} \end{pmatrix} = \begin{pmatrix} b_{11} & b_{12} & b_{13} & b_{14} & b_{15} & b_{16} \\ b_{21} & b_{22} & b_{23} & b_{24} & b_{25} & b_{26} \end{pmatrix} \tag{3.2}$$

where $m = 1, \ldots, 6$; $n = 1,2$; $\sum_{i=1}^{m} a_i = 1$; and $\sum_{k=1}^{n} b_{1k} = \sum_{k=1}^{n} b_{2k} = 1$.

The one-step transition probability matrix (P) for the observable states can be obtained through Equation (3.3). The stationary probability distribution of P is regarded as the vector p, which is expressed as Equation (3.4).

$$P = (a_1, a_2)^T \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} & b_{15} & b_{16} \\ b_{21} & b_{22} & b_{23} & b_{24} & b_{25} & b_{26} \end{bmatrix} \tag{3.3}$$

$$p = \left(\sum_{i=1}^{m} a_i b_{i1}, \sum_{i=1}^{m} a_i b_{i2}, \sum_{i=1}^{m} a_i b_{i3}, \sum_{i=1}^{m} a_i b_{i4}, \sum_{i=1}^{m} a_i b_{i5}, \sum_{i=1}^{m} a_i b_{i6}\right)^T \tag{3.4}$$

where $\sum_{k=1}^{n} p_k = 1$ and $pP = p$.

In this HMM, the objective is to predict success probability (a). Success probability (a), as an output, is associated with six inputs, i.e., the six evaluation criteria. Suppose m, n, B, and the observed distribution (Q) are given, the probability of the hidden states (a) can be resolved. Q is the normalized values obtained from the evaluation scorecard for each idea. For simplicity, ordinary least squares analysis is chosen to estimate the unknown probability (a). Ordinary least squares analysis is considered a less complex but more effective way to solve the problem, i.e., to determine the unknown parameter and obtain its optimal value. This is supported by Scott and Holt (1982) and Puntanen and Styan (1989). The former found that the ordinary least squares estimation often performs well and is fairly efficient while the latter stated that the ordinary least squares analysis is well-known and can become a best linear unbiased estimator. In this research, ordinary least squares analysis is used to minimize the sum of squared distances between the vector p and the distribution Q. The goodness-of-fit of the ordinary least squares analysis can be assessed by Pearson's coefficient of determination, R^2, for the sake of verification.

The success probability (a) can be estimated by solving the following minimization problem based on the ordinary least squares analysis:

$$\min \sum_{k=1}^{n}(p-Q)^2 = \min \sum_{k=1}^{n}\left[\sum_{i=1}^{m} a_i b_{ik} - q_k\right]^2 \text{ subject to } 0 \le a \le 1 \qquad (3.5)$$

where $a = \begin{cases} 0, & a \le 0 \\ a, & 0 < a < 1 \\ 1, & a \ge 1 \end{cases}$, and $Q = (q_1, \cdots, q_n)$.

The goodness-of-fit can be assessed through the following:

$$R^2 = 1 - \sum_{k=1}^{n}(p_k - q_k)^2 / \sum_{k=1}^{n}(p_k - \bar{p})^2 \qquad (3.6)$$

where $0 \leq R^2 \leq 1$, and when the values of R^2 is close to 1, it represents better goodness-of-fit.

Phase 2: Data collected by the evaluation scorecard, i.e., ratings of each criterion for each new product idea, can be divided into two subsets: training data set and testing data set. Two-thirds of the data, i.e., the training data set, are used to train the HMM designed in phase 1 in order to estimate the parameter set of the training HMM. Based on the training data set, the state probability distribution is determined through Equation (3.4). The expected success probability of each new product idea is determined through Equation (3.5). Then it assists in ascertaining the cut-off value that separates successful new product ideas from the worthless ones. In other words, the optimal cut-off value for making go or kill decisions can be obtained in the training HMM.

Phase 3: Another subset of data, i.e., the testing data set, is used to test the accuracy of the training HMM for the sake of validation. The expected success probability of each new product idea in the testing data set is computed, and an NPIS decision, either a go or kill decision, is made accordingly. If the NPIS decisions based on the training HMM match the actual decisions in reality, and if the cut-off value in the testing HMM is consistent with that in the training model, Module I can be proven to be valid for the sake of NPIS decision making.

3.3 Case Study

Module I can facilitate the classification of new product ideas. It is used to screen new product ideas and classify them into the successful ones, which lead to go decisions, and worthless ones, which lead to kill decisions.

Data

A case study is carried out to illustrate the application of Module I. Data collected from the case company are presented in this section. The case company is a world-class leader in the power tool industry. It offers high-quality, innovative, and professional products, which are marketed worldwide, for home improvement and construction industries. Since the case company is particularly famous for its electric drills, 76 new product ideas of them launched then were collected for this case study. Such data were extracted to be studied as long as it is related to the five criteria on the scorecard. Two-thirds of the data (as training data set) were used in the application of Module I while one-third (as testing data set) were used in the validation of Module I. Apart from data collection, an interview with five NPD experts was conducted to support the development of Module I. The experts are the key decision-makers involved in the screening of new product ideas, and they are directors from the functions of quality, marketing, engineering, manufacturing, and supply chain of the case company.

3.3.1 Application of the Idea Screening Decision Model

In this case study, Module I is used to support NPIS decisions. Before determining the success probability of new product ideas, appraising these ideas through the evaluation scorecard is necessary. The scorecard is firstly approved by the five NPD experts of the case company. The experts agreed that it is reasonable and accurate enough to evaluate new product ideas on the five-point scale, on which respective interpretations are made. They also confirmed the framework of the scorecard. As they originally use only linguistic terms, which are unquantifiable and incomparable, to evaluate new product ideas based on multiple criteria, data of 76 ideas are used and converted into quantitative variables on the five-point scale according to the evaluation scorecard. As described in Figure 3.1, the results of the evaluation of new product ideas, i.e., the rating of each criterion of the 76 new product ideas, are used as inputs of the HMM. Therefore the results are normalized and divided into two subsets, which are the training data set and testing data set shown in Table 3.4 and Table 3.6, respectively.

After the results are obtained from the evaluation scorecard, the HMM can then be applied to determine the success probabilities of the 76 new product ideas. As this case study is related to NPIS, two hidden states ($n = 2$) and six observable states ($m = 6$) are considered. The stationary distribution of the observable states in the training HMM is shown in Table 3.3 based on the training data set in Table 3.4. It is obtained by calculating the average possibility of each criterion on the scorecard. The data in Table 3.4 are the given normalization results of ratings based on a five-point scale on the scorecard. The normalized values in Table 3.4 constitute the observed distribution (Q). As mentioned earlier, given m, n, B, and the observed distribution (Q), the probability of the hidden states (a) in Equation (3.1) can be resolved. By solving the minimization problem through Equation (3.5), the success probability (a)

for each new product idea is obtained and shown in Table 3.5.

If the success probability is higher, a go decision is more likely to be made. From Table 3.5, it is observed that the range of a with a hidden state $s_1 = Go$ is [0.53, 1], while that with a hidden state $s_2 = Kill$ is [0, 0.51]. This implies that NPIS decisions can certainly be made based on these two intervals, which suggest the optimal range of the success probability and distinguish ideas between go and kill decisions. The value of R^2 of this training HMM is estimated as 0.9992 through Equation (3.6), and the value indicates that the training HMM is best-fit and the most meaningful. This HMM can certainly determine the hidden states of new product ideas.

Table 3.3 Stationary distribution of idea evaluation

	CN	**MS**	**TC**	**MANU**	**LDS**	**RB**
s_1	0.16	0.17	0.16	0.17	0.17	0.16
s_2	0.11	0.13	0.13	0.11	0.11	0.41

Table 3.4 Two-thirds of the data set used for model application

$s_1 = Go$

Idea	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
CN	0.16	0.16	0.2	0.16	0.2	0.12	0.2	0.16	0.16	0.16	0.2	0.12	0.12	0.16	0.16	0.12	0.16	0.2	0.12	0.16	0.16	0.16	0.16	0.2	0.16	0.2	0.16	0.16	0.16	0.2	0.16
MS	0.12	0.16	0.16	0.2	0.2	0.16	0.16	0.2	0.2	0.2	0.2	0.16	0.16	0.16	0.2	0.16	0.2	0.2	0.12	0.16	0.2	0.12	0.16	0.16	0.12	0.2	0.12	0.2	0.2	0.16	0.16
COMP	0.16	0.16	0.16	0.12	0.2	0.16	0.2	0.12	0.2	0.08	0.2	0.12	0.16	0.2	0.16	0.2	0.16	0.16	0.16	0.12	0.12	0.2	0.2	0.16	0.16	0.2	0.12	0.08	0.16	0.16	0.2
MANU	0.2	0.2	0.2	0.16	0.2	0.12	0.16	0.2	0.2	0.16	0.2	0.16	0.2	0.08	0.08	0.16	0.2	0.16	0.2	0.12	0.16	0.2	0.16	0.16	0.2	0.2	0.2	0.12	0.2	0.16	0.16
DC	0.2	0.12	0.16	0.2	0.16	0.16	0.2	0.2	0.2	0.2	0.16	0.2	0.2	0.2	0.16	0.12	0.2	0.2	0.12	0.2	0.16	0.12	0.16	0.12	0.16	0.2	0.2	0.2	0.2	0.16	0.16
RB	0.16	0.2	0.12	0.16	0.04	0.28	0.08	0.12	0.04	0.2	0.04	0.24	0.16	0.2	0.24	0.24	0.08	0.08	0.28	0.24	0.2	0.2	0.16	0.2	0.2	0	0.2	0.24	0.08	0.16	0.16

$s_2 = Kill$

Idea	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
CN	0.16	0.12	0.08	0.12	0.08	0.04	0.08	0.12	0.16	0.16	0.04	0.12	0.16	0.04	0.12	0.08	0.16	0.12	0.16	0.08
MS	0.16	0.12	0.12	0.2	0.12	0.04	0.12	0.2	0.2	0.12	0.04	0.16	0.12	0.04	0.16	0.08	0.16	0.08	0.2	0.12
COMP	0.08	0.12	0.12	0.16	0.16	0.12	0.12	0.16	0.16	0.16	0.08	0.04	0.2	0.12	0.16	0.2	0.08	0.16	0.08	0.2
MANU	0.04	0.16	0.12	0.08	0.12	0.08	0.16	0.12	0.12	0.08	0.08	0.04	0.12	0.16	0.12	0.12	0.12	0.12	0.08	0.12
DC	0.04	0.16	0.12	0.08	0.16	0.12	0.08	0.12	0.08	0.12	0.12	0.08	0.12	0.08	0.12	0.08	0.12	0.08	0.12	0.12
RB	0.52	0.32	0.44	0.36	0.36	0.6	0.44	0.28	0.28	0.36	0.64	0.56	0.28	0.56	0.32	0.44	0.36	0.44	0.36	0.36

Table 3.5 Resulting values of a of the training model

$s_1 = Go$																															
Idea	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
a	1	0.84	1	1	1	0.53	1	1	1	0.88	1	0.71	1	0.83	0.67	0.67	1	1	0.53	0.7	0.85	0.83	0.99	0.84	0.86	1	0.88	0.71	1	1	0.99

$s_2 = Kill$																				
Idea	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
a	0	0.39	0	0.19	0.22	0	0	0.51	0.5	0.2	0	0	0.51	0	0.36	0	0.23	0	0.22	0.19

3.3.2 Validation of the Idea Screening Decision Model

Although the value of R^2, i.e., 0.9992, of the training HMM confirms that the HMM is best-fit and the most meaningful, further validation of the HMM is needed to prove its efficiency. As mentioned above, one-third of the data, i.e., the testing data set, regarding the assessment results of new product ideas are used in the validation of the HMM. The testing data set is shown in Table 3.6.

Following the procedures taken to formulate the training HMM, the testing HMM can be established for the sake of validation. The resulting values of a of this testing HMM are calculated and shown in Table 3.7. Referring to the training HMM, a go decision is to be made if the value of a is in the interval [0.53, 1], and a kill decision is to be made if the value is in the interval [0, 0.51]. Table 3.7 reveals that the resulting values of a in the testing HMM conform to that in the training HMM. It is interpreted that the training HMM determines the hidden states of new product ideas correctly. Using the value of a, i.e., the success probability, to support NPIS decision making is therefore convincing. Furthermore, the value of R^2 of the testing HMM is estimated to be 0.96, which is close to 1 and indicates that the testing HMM is best-fit and effective. Module I is thus proven to be valid and significant in making NPIS decisions.

Table 3.6 One-third of the data set used for model validation

$s_1 = Go$															
Idea	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
CN	0.2	0.16	0.16	0.12	0.16	0.2	0.16	0.16	0.16	0.12	0.16	0.2	0.16	0.2	0.16
MS	0.2	0.16	0.2	0.16	0.2	0.16	0.12	0.16	0.2	0.16	0.16	0.16	0.12	0.2	0.2
COMP	0.16	0.2	0.16	0.12	0.16	0.16	0.16	0.12	0.12	0.12	0.2	0.16	0.16	0.2	0.08
MANU	0.16	0.2	0.08	0.16	0.2	0.12	0.2	0.16	0.16	0.12	0.16	0.16	0.2	0.2	0.12
DC	0.16	0.2	0.16	0.16	0.2	0.16	0.12	0.2	0.16	0.2	0.16	0.12	0.16	0.16	0.2
RB	0.12	0.08	0.24	0.28	0.08	0.2	0.24	0.2	0.2	0.28	0.16	0.2	0.2	0.04	0.24

$s_2 = Kill$										
Idea	1	2	3	4	5	6	7	8	9	10
CN	0.08	0.12	0.12	0.16	0.16	0.08	0.12	0.16	0.04	0.12
MS	0.12	0.12	0.2	0.2	0.12	0.08	0.16	0.12	0.04	0.16
COMP	0.16	0.16	0.16	0.16	0.16	0.2	0.04	0.2	0.12	0.16
MANU	0.16	0.16	0.12	0.12	0.08	0.16	0.04	0.12	0.16	0.12
DC	0.16	0.12	0.12	0.08	0.12	0.16	0.08	0.12	0.08	0.12
RB	0.32	0.32	0.28	0.28	0.36	0.32	0.56	0.28	0.56	0.32

Table 3.7 Resulting values of a of the testing model

$s_1 = Go$															
Idea	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
a	1	1	0.67	0.54	1	0.84	0.69	0.87	0.85	0.55	0.99	0.84	0.86	1	0.71

$s_2 = Kill$										
Idea	1	2	3	4	5	6	7	8	9	10
a	0.38	0.37	0.51	0.50	0.20	0.37	0	0.51	0	0.36

3.4 Chapter Summary

To facilitate NPIS decision making in a more efficient and certain manner, Module I: an idea screening decision model is established and proven to be effective through a case study. The value of R^2 of the HMM, being close to 1, further confirms that the HMM is meaningful and best-fit. This further supports that Module I is thus useful for NPIS. In Module I, the scorecard can serve as a guide for new product idea evaluation, converting experts' linguistic judgments to quantifiable and comparable data; whereas the HMM can determine the success probability of new product ideas to support NPIS decision making based on the computed evaluation performance. The optimal cut-off value for making either a go or kill decision on each idea can thus be determined.

The case study has fully illustrated and verified the application of Module I to NPIS. This addresses the problem identified in Problem Statement A in Chapter 1. The case study is valuable in that it determines the optimal intervals for the case company to make go or kill decisions on all ideas. A go decision should be made when the probability lies in the interval [0.53, 1]. The figure is important, and the directors of the case company consented that Module I is useful to prevent them from developing worthless new product ideas, and to choose the more competitive ones toward commercialization, thus enhancing the success rate of NPD. Besides, the case study presented in this chapter can provide guidance for companies on using Module I, which can be customized to cope with the situations and needs of different companies.

Furthermore, Module I contributes to resolve the four difficulties mentioned in Chapter 2.3.1 and the following major problems concerning NPIS.

(i) *To evaluate new product ideas based on easily obtained managerial judgments in linguistic terms and also the past NPD project experience:*

This provides more concrete information to determine probabilities of success and the optimal success value for NPIS decision making.

(ii) *To evaluate new product ideas analytically through the evaluation scorecard:*

The scorecard (refer to Table 3.2) comprises five criteria based on a five-point scoring scale; there are different definitions with respect to each criteria on the five-point scoring scale. This scorecard not only guides experts through the new product idea evaluation process but also makes linguistic terms and qualitative evaluation criteria quantifiable and comparable. This in turn enhances the communication among experts who speak different languages, thereby reducing conflicts. This also helps aggregate experts' judgments and make vague judgments solid.

(iii) *To include risk buy (RB) in the HMM:*

It is risky to use vague information and make conjectures without solid basis. Module I, however, permits managers to fully consider all information in order to make more justifiable decisions. The uncertainties of making such decisions without sufficient and concrete information are addressed by including RB in the HMM. Furthermore, RB also accounts for the highly uncertain environment due to fast-changing market needs and rapid technological innovation.

(iv) *To determine the success probability of new product ideas and discover the optimal intervals to differentiate potentially successful ideas from worthless ones for NPIS decision making:*

These values are obtained through the HMM with the computation of the evaluation scores of new product ideas. It is helpful in supporting managers to determine which ideas should be selected and which killed for making go or kill decisions effectively.

To conclude, Module I is unique and original because of the six distinctive factors, as well as the integration of the evaluation scorecard and the HMM. Performing NPIS for all new product ideas through Module I is novel and practical, and the extant literature has not delved into the matter, making Module I significant.

CHAPTER 4 A CUSTOMER PERCEPTION MODEL FOR PRIORITIZING PRODUCT CHARACTERISTICS

4.1 Introduction

The previous chapter described Module I: an idea screening decision model of the proposed iDSS. Module I facilitates managers to evaluate new product ideas within the company from the experts' perspective, and then to determine their success probabilities to support new product ideas screening (NPIS) decision making for all new product ideas. The case study has further demonstrated that Module I is effective and practical.

As mentioned previously, customers' involvement and the voice of customers are necessities of new product development (NPD) and the new products that are best-fit are launched to fulfill customers' actual needs. Apart from evaluating the new product ideas internally, it is necessary to explore the customers' perceptions and include their judgments for further assessment. In this chapter, Module II: a customer perception model of the proposed iDSS is introduced. Unlike Module I, Module II centers on the perspective of customers rather than that of experts. It is to weigh and prioritize product characteristics from the customers' perspective by investigating their buying decisions through a customer survey. The framework and development of Module II is firstly introduced in this chapter. Applying Module II, a case study that illustrates the prioritization of product characteristics, which is equivalent to that of customer requirements, is then discussed.

In reality, companies intend to deliver new products that motivate customers to make purchases, thereby capturing value from those customers. Customer buying decisions primarily rest on such product characteristics as product attributes, product packaging, time to market, and brand. However, there is often a trade-off among these characteristics in NPD. With regard to this multi-attribute decision, a fuzzy analytic hierarchy process (FAHP) approach with a judgment matrix that utilizes the eigenvector method is presented and employed in this research. It is to determine the priority of product characteristics in the power tool industry. Module II is significant, as the data that were collected and analyzed are all from customers, rather than from experts or decision-makers. Such a perspective is rare in the existing literature, but is absolutely helpful in supporting NPD decisions. The results of Module II are used in Module III to evaluate NPD projects.

4.2 Theoretical Framework and Development of the Customer Perception Model

Understanding and identifying customers' actual needs is an essential prerequisite for successful NPD. Companies generally collect customers' feedbacks through surveys and focus groups, and then analyze survey data and linguistic feedbacks, which result in useful information, such as rankings of end-users' needs, satisfaction ratings, and most desired characteristics. Some product characteristics are highlighted and efforts can be given to improve these characteristics, so that customers would be more satisfied. Gaining insights into customer needs is significant but companies often fail to adopt any knowledge systems and analytical approaches to interpret customer needs. As discussed in Chapters 1 and 2, FAHP is a popular and powerful technique to tackle multi-attribute decision-making problems. Its applications have been discussed in Chapters 1 and 2 and can be found in the literature (Buckley, 1985; Cheng and Mon, 1994; Chen, 2000; Csutora and Buckley, 2001; Kwong and Bai, 2002; Mikhailov, 2003; Lau *et al.*, 2006). It is found in this discussion that FAHP is an effective approach to help companies rank customer needs and formulate the NPD strategy. It is therefore applied to the construction of Module II.

This section describes the theoretical framework and development of the customer perception model with the support of an extended FAHP algorithm. The extended FAHP algorithm developed in this research is on the basis of FAHP proposed by Kwong and Bai (2002), and is integrated with the geometric mean method. This integration helps synthesize the opinions of a group of customers before developing the fuzzy judgment matrices. Supported by many researchers (Lootsma, 1996; Van-Den-Honert and Lootsma, 1996; Hovanov *et al.*, 2008; Tseng *et al.*, 2008), the geometric mean method is an efficient and accurate way to combine group opinions into a collective opinion. The researchers did use the geometric mean method for group decision making. There are six steps to determine the priority of product characteristics. The integration of the geometric mean method is indicated at step 3. The six steps are as follows:

1. To construct a hierarchical structure of product characteristics;
2. To collect customers' opinions using a pairwise comparison technique;
3. To synthesize customers' opinions and translate them into triangular fuzzy numbers;
4. To construct fuzzy judgment matrices;
5. To calculate corresponding eigenvectors of the fuzzy matrices; and

6. To determine the finalized weight of each element in the hierarchical structure.

The six steps of the extended FAHP algorithm in Module II are discussed in detail below:

Step 1: A hierarchical structure with different levels of product characteristics has to be constructed. Interviews with industrial experts and discussion among them could help perform this task. The structure of a hierarchy is demonstrated below.

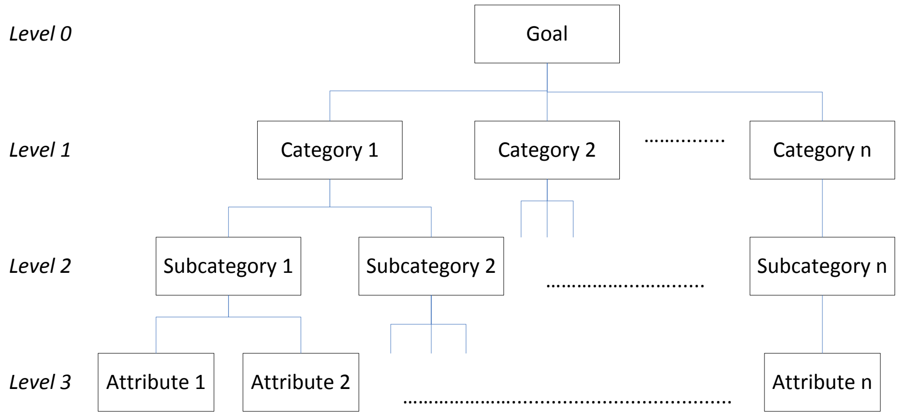


Figure 4.1 Hierarchical structure

Step 2: A ratio scale for pairwise comparison is needed to evaluate product characteristics. The nine-point scale established by Saaty (1980) is frequently used in the conventional analytic hierarchy process (AHP). It is employed in Module II (see Table 4.1), as it appears to be an optimal scale by which decision-makers can compare elements and express their preferences in crisp real numbers (Triantaphyllou, 2000). As Module II is to hear the voice of customers, a customer survey is suggested to be carried out. This is because it is often a popular and effective way to explore customers' perceptions on product characteristics in NPD.

However, the customer survey that is used in Module II should be designed with pairwise comparison based on the product characteristics identified in the hierarchical structure.

Table 4.1 Scale and interpretation of pairwise comparison

Nine-point scale	Interpretation/Linguistic term
1	Equally important
3	Moderately important
5	Strongly important
7	Very strongly important
9	Extremely important
2,4,6,8	Intermediate values between the two adjacent judgments

Step 3: After collecting customers' opinions, their opinions can be synthesized and generalized by the geometric mean method. According to Dyer and Forman (1992), the consensus, vote, geometric mean, and separate model are methods used to incorporate judgments of a group of people for the sake of group decision making. Among these methods, the geometric mean method is adopted here because it is found to be easily integrated with FAHP. Furthermore, as discussed before, the geometric mean method is appropriate for combining group opinions into a collective opinion. The calculation of the geometric mean is expressed as Equation (4.1).

In addition, to translate customers' opinions into fuzzy numbers, a triangular fuzzy membership function, which is presented as Equation (4.2), is employed.

$$g_i = \left[\prod_{j=1}^{n} x_{ij}\right]^{1/n} \tag{4.1}$$

$$\mu_{\widetilde{M}}(x) = \begin{cases} \frac{x-a}{b-a}, & x \in [a,b] \\ \frac{c-x}{c-b}, & x \in [b,c] \\ 0, & otherwise \end{cases} \tag{4.2}$$

where g is the corresponding geometric mean value; x is customers' opinions in terms of the nine-point scale; $\widetilde{M} = (a,b,c)$ is denoted as a set of triangular fuzzy numbers defined by three real numbers as (a,b,c); and a, b and c represent the lower, middle, and upper values, respectively, of fuzzy number $\widetilde{M}_i$, where $a \leq b \leq c$ and $i = 1,2,\ldots,n$.

A discussion about the triangular fuzzy membership function is provided to supplement the above equations. The fuzzy theory plays an important role in dealing with ambiguities in a system (Zimmermann, 1996) and has been applied to a variety of decision models. There are four common special forms of fuzzy numbers: L-R triangular numbers, L-R trapezoidal numbers, triangular fuzzy numbers, and trapezoidal fuzzy numbers. Each form of fuzzy number has an algebraic formula. Triangular fuzzy numbers, in particular, have been widely adopted due to their simplicity of use and accurate representation of problem features (Buckley, 1985; Chan *et al.*, 1999). These numbers are therefore applied, through the symmetric triangular membership function in this research, to represent subjective pairwise comparison and to capture the vagueness inherent in customer buying decisions and evaluations of product characteristics. To take the imprecision and subjectivity of qualitative assessments and judgments into account, the triangular fuzzy numbers $\tilde{1}$ to $\tilde{9}$ are used to represent pairwise comparison, in order to improve the conventional nine-point scale. Qualitative assessments ranging from equally preferable to extremely preferable are translated into triangular fuzzy numbers to capture the fuzzy range of human judgments. For example, a set of triangular fuzzy numbers $(\tilde{8}, \tilde{9}, \tilde{9})$ is interpreted as "extremely preferable," $(\tilde{1}, \tilde{1}, \tilde{2})$ for "equally preferable," and $(\tilde{2}, \tilde{3}, \tilde{4})$ for "moderately preferable." This fuzzy representation of pairwise comparison is defined and shown in Figure 4.2.

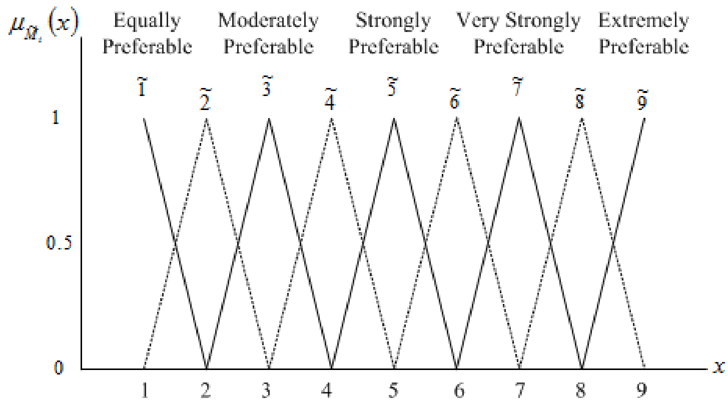


Figure 4.2 Triangular membership function

Step 4: With the help of the triangular fuzzy numbers for pairwise comparison, an $n \times n$ fuzzy comparison matrix, $\tilde{A}(\tilde{a}_{ij})$, is constructed below, i.e., Equation (4.3), in which the fuzzy number $\tilde{a}_{ij}$ eventually shows the relative importance of element i over j.

$$\tilde{A} = \begin{bmatrix} 1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1(n-1)} & \tilde{a}_{1n} \\ \tilde{a}_{21} & & & & \tilde{a}_{2n} \\ \vdots & & \ddots & & \vdots \\ \tilde{a}_{(n-1)1} & & & & \tilde{a}_{(n-1)n} \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \cdots & \tilde{a}_{n(n-1)} & 1 \end{bmatrix} \tag{4.3}$$

where $\tilde{a}_{ij} = \begin{cases} \tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9} \; or \; \tilde{1}^{-1}, \tilde{3}^{-1}, \tilde{5}^{-1}, \tilde{7}^{-1}, \tilde{9}^{-1}; & i \neq j \\ 1 \qquad ; & i = j \end{cases}$, $i = 1,2, \dots, n$ and $j = 1,2, \dots, n$.

As mentioned by Kwong and Bai (2002), with $\propto$-cuts, the fuzzy judgment matrices can be further developed by defining the interval of the confidence level, $\propto$ (see Equation 4.4), and the index of optimism, μ (see Equation 4.5). In addition, Zhu *et al.* (1999) stated that the value of $\propto$ should be larger than or equal to 0.5. The larger the values of $\propto$ and μ, the higher the degree of confidence and level of optimism. To simplify, $\propto = 0.5$ and $\mu = 0.5$ are defined in this research to satisfy both situations for the fuzzy comparison matrices. After fixing the values of $\propto$ and μ, a matrix, such as the one in Equation (4.6), can be obtained for further estimation.

$$\widetilde{M}^{\propto} = [a^{\propto}, c^{\propto}] = [(b-a)\propto + a, (b-c)\propto + c]; \ \ \forall \propto \in [0,1] \tag{4.4}$$

$$\hat{a}_{ij}^{\propto} = \mu a_{iju}^{\propto} + (1-\mu) a_{ijl}^{\propto}; \ \ \forall \mu \in [0,1] \tag{4.5}$$

$$\tilde{A} = \begin{bmatrix} 1 & \hat{a}_{12}^{\propto} & \cdots & \hat{a}_{1(n-1)}^{\propto} & \hat{a}_{1n}^{\propto} \\ \hat{a}_{21}^{\propto} & & & & \hat{a}_{2n}^{\propto} \\ \vdots & & \ddots & & \vdots \\ \hat{a}_{(n-1)1}^{\propto} & & & & \hat{a}_{(n-1)n}^{\propto} \\ \hat{a}_{n1}^{\propto} & \hat{a}_{n2}^{\propto} & \cdots & \hat{a}_{n(n-1)}^{\propto} & 1 \end{bmatrix} \tag{4.6}$$

Step 5: The corresponding eigenvectors are calculated by computing the maximal eigenvalue of the related fuzzy matrices. As Kwong and Bai (2002) noted, a fuzzy eigenvalue, $\tilde{\lambda}$, is a fuzzy number solution; thus, the following equation is formed.

$$\tilde{A}\tilde{x} = \tilde{\lambda}\tilde{x} \tag{4.7}$$

where $\tilde{A}$ is an $n \times n$ fuzzy matrix with fuzzy number $\tilde{a}_{ij}$, as previously mentioned, and $\tilde{x}$ is a non-zero $n \times 1$ fuzzy eigenvector with fuzzy numbers $\tilde{x}_i = \tilde{x}_1, \tilde{x}_2, \ldots, \tilde{x}_n$. Using interval arithmetic and $\propto$-cuts, fuzzy multiplication and addition are performed to formulate Equation (4.8), as follows:

$$[a_{i1l}^{\propto} x_{1l}^{\propto}, a_{i1u}^{\propto} x_{1u}^{\propto}] \oplus \cdots \oplus [a_{inl}^{\propto} x_{1l}^{\propto}, a_{inu}^{\propto} x_{nu}^{\propto}] = [\lambda a_{il}^{\propto}, \lambda a_{iu}^{\propto}] \tag{4.8}$$

where $\tilde{a}_{ij}^{\propto} = [\tilde{a}_{ijl}^{\propto}, \tilde{a}_{iju}^{\propto}]$, $\tilde{x}_i^{\propto} = [\tilde{x}_{il}^{\propto}, \tilde{x}_{iu}^{\propto}]$, $\tilde{\lambda}^{\propto} = [\tilde{\lambda}_l^{\propto}, \tilde{\lambda}_u^{\propto}]$ in which $0 \leq \propto \leq 1$, given that $i = 1,2, \dots, n$, and $j = 1,2, \dots, n$.

Step 6: After the decomposition of eigenvector, the normalized weights of each element at each level of the decision hierarchy are determined by normalizing the corresponding eigenvectors. After that, the finalized weight, i.e., the priority weight of each element can be determined through the calculation of the corresponding normalized weights.

4.3 Case Study

The theoretical framework and development of the customer perception model described above is applied through a case study presented in this section. Similar to other companies, the case company analyses customer needs expressed in linguistic terms, which are subjective and unquantifiable. As power tools from the case company are particularly famous, they are chosen to be examined in the customer perception model. Hence, the “products” in this case study refer to power tools. Module II: a customer perception model is applied to the case study according to the six steps given above.

A hierarchical structure with different levels of product characteristics is required in Module II. After an in-depth interview with a group of experts in the NPD team from the case company, a four-level hierarchical structure of the product characteristics that influences consumer buying decision was constructed, as shown in Figure 4.3. There are five dimensions, 13 criteria, and 19 attributes in total. These product characteristics could influence customer buying decisions.

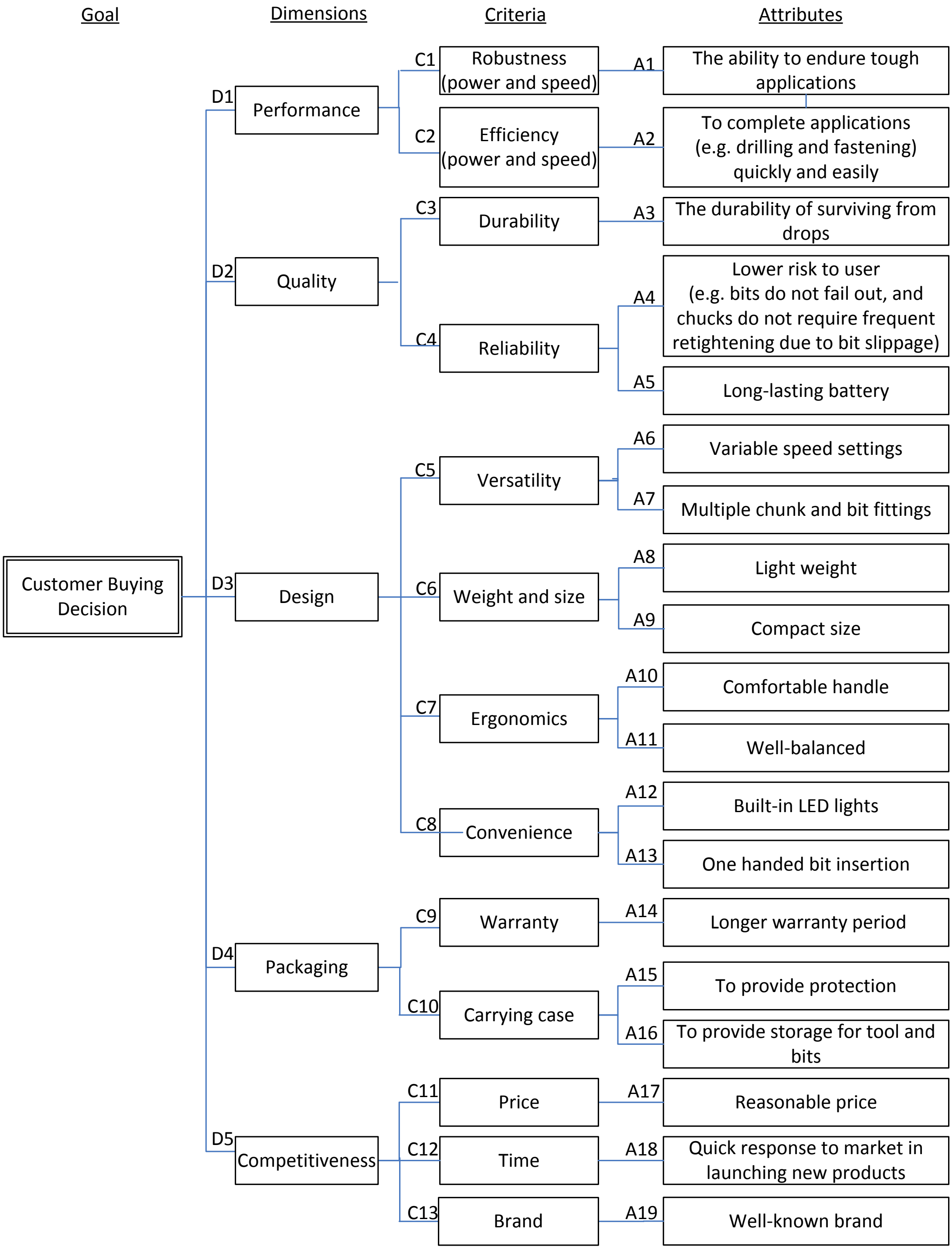


Figure 4.3 Four-level hierarchy of product characteristics of power tools

As this module focuses on the customers' perspective, as opposed to the experts' and decision-makers' perspective, only the development of the hierarchy is based on experts' opinions. A customer survey was then conducted for data collection and further analysis in this research. Based on the hierarchy shown in Figure 4.3, a customer survey using a nine-point scale for pairwise comparison (see Table 4.1) was designed to investigate how customers evaluate power tools and decide to buy them. The primary data were gathered among a sample of customers who have purchased and used power tools. The questionnaire is attached in Appendix B for reference. Among the 150 questionnaires distributed, 102 were completed and returned. (Please refer to Chapter 2 for the details of customer survey.)

Based on the results of the survey, customers' opinions are synthesized, and relevant fuzzy comparison matrices, $FCM_i^{0.5}$, are established, as shown in Table 4.2, using the geometric mean method (Equation 4.1) and triangular fuzzy numbers (Equation 4.2). The lower and upper values of the fuzzy numbers are obtained by $\propto$-cut analysis, provided that $\propto = 0.5$.

Table 4.2 Fuzzy comparison matrices obtained from the survey results

	$FCM_1^{0.5}$	
	A4	A5
A4	(1,1,1)	(0.59,0.75,1.11)
A5	(0.90,1.34,1.69)	(1,1,1)
	$FCM_2^{0.5}$	
	A6	A7
A6	(1,1,1)	(1.11,1.43,1.93)
A7	(0.52,0.70,0.90)	(1,1,1)
	$\mathrm{FCM}_3^{0.5}$	
	A8	A9
A8	(1,1,1)	(0.83,1.00,1.46)
A9	(0.69,1.00,1.20)	(1,1,1)
	$FCM_4^{0.5}$	
	A10	A11
A10	(1,1,1)	(0.76,0.89,1.12)
A11	(0.89,1.13,1.33)	(1,1,1)
	$FCM_5^{0.5}$	
	A12	A13
A12	(1,1,1)	(0.46,0.57,0.76)
A13	(1.32,1.74,2.18)	(1,1,1)

(To be continued on the next page)

Table 4.2 Fuzzy comparison matrices obtained from the survey results

$FCM_6^{0.5}$		
	A15	A16
A15	(1,1,1)	(0.68,0.84,1.20)
A16	(0.83,1.19,1.47)	(1,1,1)

$FCM_7^{0.5}$		
	C1/A1	C2/A2
C1/A1	(1,1,1)	(0.43,0.53,0.68)
C2/A2	(1.47,1.90,2.32)	(1,1,1)

$FCM_8^{0.5}$		
	C3	C4
C3	(1,1,1)	(1.63,2.10,2.68)
C4	(0.37,0.48,0.61)	(1,1,1)

$\mathrm{FCM}_9^{0.5}$				
	C5	C6	C7	C8
C5	(1,1,1)	(0.78,0.95,1.27)	(0.83,0.98,1.28)	(0.60,0.75,1.05)
C6	(0.79,1.05,1.28)	(1,1,1)	(0.64,0.77,0.98)	(1.45,1.90,2.56)
C7	(0.78,1.02,1.21)	(1.02,1.30,1.56)	(1,1,1)	(1.02,1.27,1.65)
C8	(0.95,1.33,1.67)	(0.39,0.53,0.69)	(0.61,0.79,0.98)	(1,1,1)

$FCM_{10}^{0.5}$		
	C9	C10
C9	(1,1,1)	(1.31,1.61,2.20)
C10	(0.45,0.62,0.76)	(1,1,1)

(To be continued on the next page)

Table 4.2 Fuzzy comparison matrices obtained from the survey results

$FCM_{11}^{0.5}$			
	C11/A17	C12/A18	C13/A19
C11/A17	(1,1,1)	(1.15,1.46,1.83)	(0.91,1.10,1.47)
C12/A18	(0.55,0.68,0.87)	(1,1,1)	(0.54,0.69,0.90)
C13/A19	(0.68,0.91,1.10)	(1.11,1.45,1.85)	(1,1,1)

$FCM_{12}^{0.5}$					
	D1	D2	D3	D4	D5
D1	(1,1,1)	(0.88,1.02,1.32)	(2.00,2.40,3.08)	(1.37,1.72,2.18)	(1.21,1.46,1.81)
D2	(0.76,0.98,1.14)	(1,1,1)	(0.89,1.06,1.39)	(2.34,2.86,3.49)	(2.77,3.36,4.25)
D3	(0.32,0.42,0.50)	(0.72,0.95,1.12)	(1,1,1)	(0.66,0.81,1.07)	(0.80,0.94,1.34)
D4	(0.46,0.58,0.73)	(0.29,0.35,0.43)	(0.94,1.24,1.51)	(1,1,1)	(0.42,0.53,0.75)
D5	(0.55,0.69,0.82)	(0.24,0.30,0.36)	(0.75,1.06,1.25)	(1.33,1.88,2.41)	(1,1,1)

Given that $\mu = 0.5$, the corresponding crisp values, $\hat{a}_{ij}^{\propto}$, of the related fuzzy comparison matrices, $FCM_i^{0.5}$, can be estimated, and the latter can be converted to the following crisp comparison matrices, $CCM_i^{0.5}$. The estimation of the corresponding crisp values, $\hat{a}_{ij}^{\propto}$ is based on Equation (4.5). By solving a characteristic equation of $\det(CCM_i^{0.5} - \lambda I) = 0$, where $i = 1,2,\ldots,12$, followed by substituting λ_{max} into Equation (4.7), the corresponding eigenvectors of $CCM_i^{0.5}$, $\tilde{x}_i$, can be calculated as follows:

$$CCM_1^{0.5} = \begin{bmatrix} 1 & 0.8518 \\ 1.2953 & 1 \end{bmatrix};\ \lambda_{max} = 2.0504; \tilde{x}_1 = (0.6299, 0.7767)^T$$

$$CCM_2^{0.5} = \begin{bmatrix} 1 & 1.5172 \\ 0.7114 & 1 \end{bmatrix};\ \lambda_{max} = 2.0389; \tilde{x}_2 = (0.8251, 0.5650)^T$$

$$CCM_3^{0.5} = \begin{bmatrix} 1 & 1.1453 \\ 0.9426 & 1 \end{bmatrix};\ \lambda_{max} = 2.0390; \tilde{x}_{10} = (0.7406, 0.6719)^T$$

$$CCM_4^{0.5} = \begin{bmatrix} 1 & 0.9380 \\ 1.1083 & 1 \end{bmatrix};\ \lambda_{max} = 2.0196; \tilde{x}_4 = (0.6770, 0.7359)^T$$

$$CCM_5^{0.5} = \begin{bmatrix} 1 & 0.6088 \\ 1.7478 & 1 \end{bmatrix};\ \lambda_{max} = 2.0315; \tilde{x}_5 = (0.5083, 0.8612)^T$$

$$CCM_6^{0.5} = \begin{bmatrix} 1 & 0.9414 \\ 1.1500 & 1 \end{bmatrix};\ \lambda_{max} = 2.0405; \tilde{x}_6 = (0.6709, 0.7415)^T$$

$$CCM_7^{0.5} = \begin{bmatrix} 1 & 0.5555 \\ 1.8962 & 1 \end{bmatrix};\ \lambda_{max} = 2.0263; \tilde{x}_7 = (0.4760, 0.8794)^T$$

$$CCM_8^{0.5} = \begin{bmatrix} 1 & 2.1530 \\ 0.4938 & 1 \end{bmatrix};\ \lambda_{max} = 2.0311; \tilde{x}_8 = (0.9019, 0.4319)^T$$

$$CCM_9^{0.5} = \begin{bmatrix} 1 & 1.0246 & 1.0559 & 0.8247 \\ 1.0358 & 1 & 0.8098 & 2.0052 \\ 0.9933 & 1.2903 & 1 & 1.3360 \\ 1.3108 & 0.5404 & 0.7917 & 1 \end{bmatrix};\ \lambda_{max} = 4.1924;$$

$$\tilde{x}_9 = (0.4670, 0.5543, 0.5455, 0.4309)^T$$

$$CCM_{10}^{0.5} = \begin{bmatrix} 1 & 1.7575 \\ 0.6084 & 1 \end{bmatrix};\ \lambda_{max} = 2.0341; \tilde{x}_{10} = (0.8619, 0.5071)^T$$

$$CCM_{11}^{0.5} = \begin{bmatrix} 1 & 1.4909 & 1.1902 \\ 0.7075 & 1 & 0.7231 \\ 0.8888 & 1.4754 & 1 \end{bmatrix};\ \lambda_{max} = 3.0609;$$

$$\tilde{x}_{11} = (0.6661, 0.4400, 0.6023)^T$$

$$CCM_{12}^{0.5} = \begin{bmatrix} 1 & 1.0996 & 2.5397 & 1.7734 & 1.5136 \\ 0.9473 & 1 & 1.1439 & 2.9127 & 3.5073 \\ 0.4126 & 0.9180 & 1 & 0.8643 & 1.0673 \\ 0.6952 & 0.3574 & 1.2250 & 1 & 0.5846 \\ 0.6880 & 0.2984 & 0.9999 & 1.8673 & 1 \end{bmatrix};\ \lambda_{max} = 5.3526;$$

$$\tilde{x}_{12} = (0.5652, 0.6392, 0.3187, 0.2623, 0.3189)^T$$

The normalized weights of each element of the product characteristics in each of the four levels are determined after normalization of the related eigenvectors, as follows:

$C_3: (w_{A4}, w_{A5}) = (0.4478, 0.5522)$

$C_5: (w_{A6}, w_{A7}) = (0.5936, 0.4064)$

$C_6: (w_{A8}, w_{A9}) = (0.5243, 0.4757)$

$C_7: (w_{A10}, w_{A11}) = (0.4792, 0.5208)$

$C_8: (w_{A12}, w_{A13}) = (0.3711, 0.6289)$

$C_{10}: (w_{A15}, w_{A16}) = (0.4750, 0.5250)$

$D_1: (w_{C1}, w_{C2}) = (w_{A1}, w_{A2}) = (0.3512, 0.6488)$

$D_2: (w_{C3}, w_{C4}) = (0.6762, 0.3238)$

$D_3: (w_{C5}, w_{C6}, w_{C7}, w_{C8}) = (0.2350, 0.2789, 0.2744, 0.2117)$

$D_5: (w_{C11}, w_{C12}, w_{C13}) = (w_{A17}, w_{A18}, w_{A19})(0.3899, 0.2575, 0.3525)$

$Goal: (w_{D1}, w_{D2}, w_{D3}, w_{D4}, w_{D5}) = (0.2686, 0.3038, 0.1514, 0.1246, 0.1515)$

The finalized weight, i.e., priority weight, of each element of the product characteristics in each of the four levels is determined as shown in Table 4.3. Based on these results, the product characteristics can be prioritized to examine the relative importance weights of each element for the development of new power tools. Table 4.3 reveals that product performance, product quality, and product competitiveness are the three most important dimensions that customers consider during product selection, whereas product packaging and product design are the least. It is also found that durability (the durability of surviving from drops), efficiency (to complete applications quickly and easily), and robustness (the ability to endure tough applications) are the top three criteria considered by customers when buying power tools, whereas multiple built-in LED lights, chunk and bit fittings, and a comfortable handle are the least. These results indicate the appropriate rankings and trade-offs among the key product characteristics of power tools, and thus provide companies with an insight into the design of new products of power tools. This enables companies to launch more attractive and competitive products to stimulate customer buying decisions as well as to meet their actual needs. Besides, the results of this module can be input into Module III, which will be introduced in Chapter 5, to evaluate NPD projects from the perspective of customers.

Table 4.3 Weight and ranking of each element in product characteristics

Dimensions	**Criteria**	**Attributes**	**Ranking**
D1: Performance =w_{D1}=0.2686	C1: Robustness =$w_{D1} \times w_{C1}$=0.0943	A1: The ability to endure tough applications =$w_{D1} \times w_{C1} \times w_{A1}$=0.0943	3
	C2: Efficiency =$w_{D1} \times w_{C2}$=0.1743	A2: To complete applications quickly and easily =$w_{D1} \times w_{C2} \times w_{A2}$=0.1743	2
D2: Quality =w_{D2}=0.3038	C3:Durability =$w_{D2} \times w_{C3}$=0.2054	A3: The durability of surviving from drops =$w_{D2} \times w_{C3} \times w_{A3}$=0.2054	1
	C4: Reliability =$w_{D2} \times w_{C4}$=0.0984	A4: Lower risk to user =$w_{D2} \times w_{C4} \times w_{A4}$=0.0441	8
		A5: Long-lasting battery =$w_{D2} \times w_{C4} \times w_{A5}$=0.0543	6

(To be continued on the next page)

Table 4.3 Weight and ranking of each element in product characteristics

Dimensions	**Criteria**	**Attributes**	**Ranking**
D3: Design	C5:Versatility	A6: Variable speed settings	14
=w_{D3}=0.1514	=$w_{D3} \times w_{C5}$=0.0356	=$w_{D3} \times w_{C5} \times w_{A6}$=0.0211	
		A7: Multiple chunk and bit fittings	18
		=$w_{D3} \times w_{C5} \times w_{A7}$=0.0145	
	C6: Weight and size	A8: Light weight	11
	=$w_{D3} \times w_{C6}$=0.0422	=$w_{D3} \times w_{C6} \times w_{A8}$=0.0221	
		A9: Compact size	16
		=$w_{D3} \times w_{C6} \times w_{A9}$=0.0201	
	C7: Ergonomics	A10: Comfortable handle	17
	=$w_{D3} \times w_{C7}$=0.0415	=$w_{D3} \times w_{C7} \times w_{A10}$=0.0199	
		A11: Well-balanced	13
		=$w_{D3} \times w_{C7} \times w_{A11}$=0.0216	
	C8: Convenience	A12: Built-in LED lights	19
	=$w_{D3} \times w_{C8}$=0.0321	=$w_{D3} \times w_{C8} \times w_{A12}$=0.0119	
		A13: One handed bit insertion	15
		=$w_{D3} \times w_{C8} \times w_{A13}$=0.0202	

(To be continued on the next page)

Table 4.3 Weight and ranking of each element in product characteristics

Dimensions	Criteria	Attributes	Ranking
D4: Packaging =w_{D4}=0.1246	C9: Warranty =$w_{D4} \times w_{C9}$=0.0784	A14: Longer warranty period =$w_{D4} \times w_{C9} \times w_{A14}$=0.0784	4
	C10: Carrying case =$w_{D4} \times w_{C10}$ =0.0462	A15: To provide protection =$w_{D4} \times w_{C10} \times w_{A15}$=0.0219	12
		A16: To provide storage for tool and bits =$w_{D4} \times w_{C10} \times w_{A16}$=0.0242	10
D5: Competitiveness =w_{D5}=0.1515	C11: Price =$w_{D5} \times w_{C11}$=0.0591	A17: Reasonable price =$w_{D5} \times w_{C11} \times w_{A17}$=0.0591	5
	C12: Time =$w_{D5} \times w_{C12}$=0.0390	A18: Quick response to market in launching new products =$w_{D5} \times w_{C12} \times w_{A18}$=0.0390	9
	C13: Brand =$w_{D5} \times w_{C13}$=0.0534	A19: Well-known brand =$w_{D5} \times w_{C13} \times w_{A19}$=0.0534	7

4.4 Chapter Summary

This chapter introduces Module II in which FAHP is further integrated with the geometric mean method. A case study has been carried out to illustrate the application of Module II, through which customer buying decisions and their preferences with regard to the product characteristics of power tools are investigated. It is found that out of 19 product attributes (see Figure 4.3), durability, i.e., the durability of surviving from drops, is the most important factor that prompts customers to initiate a purchase, whereas the existence of built-in LED lights is the least. The weights and rankings of these attributes, which are determined by Module II, fully reflect customers' preferences with regard to product evaluation, selection, and purchase of power tools.

Unlike previous studies (Armacost *et al.*, 1994; Chan *et al.*, 1999; Zakarian and Kusiak, 1999; Vanegas and Labib, 2001; Chakraborty and Banik, 2006; Lin *et al.*, 2008) which determine product characteristics based on experts' judgments, this research focuses on customers' judgments, thus filling the research gap. Data analyzed in Module II were collected from a customer survey in which customers were asked about their experience of buying power tools. Their responses serve as valuable information for companies to analyze customer requirements by means of Module II. The results of Module II can serve two purposes. First, Module II can provide companies with the priority of product characteristics from the perspective of customers, and thus generate new product ideas. Companies can understand the rankings of customer requirements better and create new products that better fit customers and are more attractive to them, so that business growth can be enhanced. Second, the results of Module II can be input into Module III to support the evaluation of NPD projects. This issue will be discussed in the next chapter.

All in all, Module II is effective in dealing with multi-attribute decision making. This enables companies to directly listen to the voice of customers and to precisely recognize customers' actual needs so as to manufacture new products that are best-fit for customers. More importantly, this module definitely resolves the problem stated in Chapter 1. (Please refer to Problem Statement B.)

CHAPTER 5 A DYNAMIC DECISION MODEL FOR NEW PRODUCT DEVELOPMENT PROJECT APPROVAL

5.1 Introduction

The previous chapter introduced Module II. Customers' preferences on product characteristics, which are the relative importance weights of customer requirements in new product development (NPD), have been investigated. Having these results, companies can generate new products according to customer needs, and spend efforts on relatively more important product characteristics to drive customers to purchase, thus making a success in NPD.

Understanding customer needs is one of the vital elements in NPD. In recent years, companies have focused on how to enter markets and meet customer requirements by improving product characteristics to boost their market share and profits. Consequently, market-driven product design and development has become a popular topic in the literature. However, past research (Moskowitz and Kim, 1997; Herrmann *et al.*, 2000; Khoo *et al.*, 2002; Alexouda, 2005; Fung *et al.*, 2007; Hung *et al.*, 2008; Liu *et al.*, 2008) neither covers all major influencing factors that together drive customers to make purchase decisions, nor connects these various influencing factors to customer purchasing behavior. Furthermore, past studies (Matsatsinis and Siskos, 1999; Wassenaar and Chen, 2001; Alexouda, 2005; Lawson *et al.*, 2006; Kahraman *et al.*, 2007) fail to take the time value of money and on-going customer relationships into consideration. Detailed discussion regarding this can be referred to Chapters 1 and 2.

In response to these needs, this chapter introduces Module III of the proposed iDSS. Module III is developed to (a) predict customer purchasing behavior given certain product, customer, and marketing influencing factors, and (b) estimate the net customer lifetime value (NCLV) from customer purchasing behavior toward a specific product. This will not only enable decision-makers to compare alternatives and select competitive products to launch on the market, but will also improve the understanding of customer behavior toward particular products for the formulation of effective marketing strategies that increase customer loyalty and generate greater profits in the long term. Decision-makers can also make use of Module III to build up confidence in NPD in terms of idea generation and product improvement. After the discussion of the framework and development of Module III, its application is illustrated and validated through a case study.

5.2 Theoretical Framework and Development of the Dynamic Decision Model

After the screening is performed in Module I, the selected ideas can be moved to the next stage in which they will be further developed and regarded as NPD projects. As mentioned earlier, decision making at the front end of the NPD process is of paramount importance and there are not only one but also other decision gates in a NPD process. New product idea screening (NPIS) in Module I is an initial evaluation and decision-making in the NPD process. To ensure the selected ideas are worthy of further development, such as production, a detailed evaluation is needed, resulting in the establishment of Module III.

Module III considers on-going customer relationships with the company in order to further evaluate the NPD projects and provide a financial estimate, i.e., NCLV. This can be achieved by (a) predicting customer purchasing behavior in terms of product, customer, and marketing influencing factors, and (b) estimating the NCLV with regard to a specific product. Module III comprises of two sub-models: a customer purchasing behavior model (sub-model 1) and an NCLV estimation model (sub-model 2). The framework of Module III of the proposed iDSS is shown in Figure 5.1.

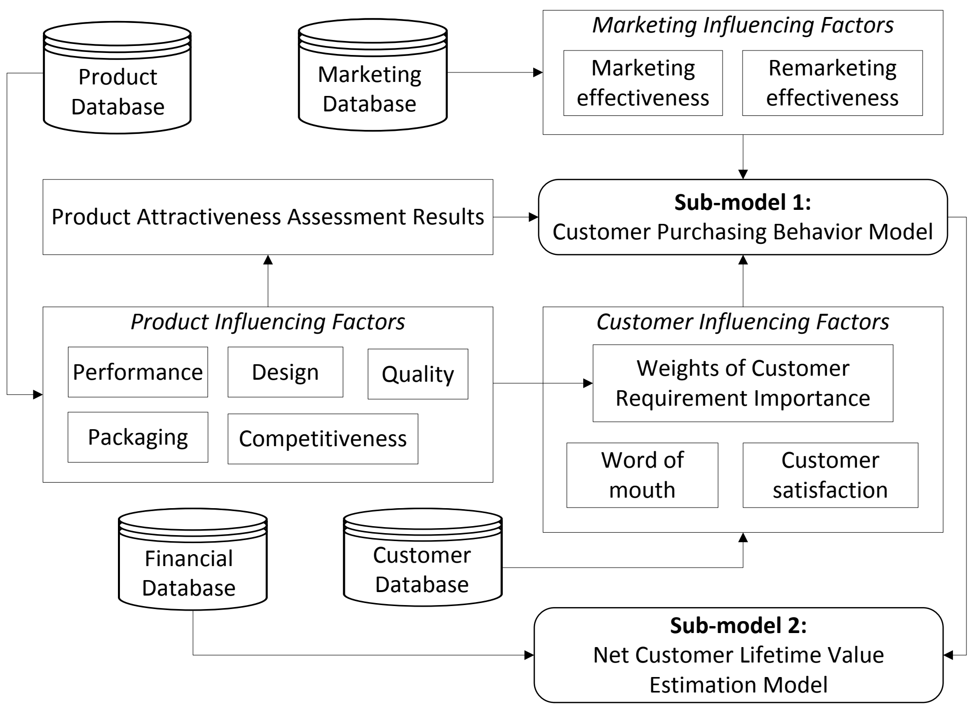


Figure 5.1 Framework of Module III of the proposed iDSS

In sub-model 1, three types of issues – product, customer, and marketing issues – are assumed to influence the dynamic behavior of customers. The three issues are identified through literature review in Chapter 2. There are various influencing factors under each type of issue. The product issue refers to product attractiveness in terms of performance, quality, design, packaging, and competitiveness. The customer issue includes the impact of word of mouth, customer satisfaction, and the relative importance of customer requirements concerning new products. The marketing issue focuses on the marketing effectiveness for potential customers and remarketing effectiveness for active customers. The parameters of the product-related factors are judged by experts in the NPD team through an assessment scorecard regarding product attractiveness, whereas the parameters of the customer-related factors are established through a customer survey and those of the marketing-related factors are obtained from a company's historical marketing data.

After predicting the customer demands through sub-model 1 and examining the financial data of the company, NCLV is estimated in sub-model 2 through Markov analysis. NCLV is defined as the sum of the present lifetime value of the future profit from customer relationships. In general, current DSSs support NPD decision making mainly based on profit maximization and transaction-based calculations. For example, Hung *et al.* (2008) selected alternatives based on development time and cost to develop an integrated information system for product design. Kahraman *et al.* (2007) proposed a decision making approach for the selection of new products based on the return maximization, in terms of profit, strategic impact, and efficiency of the development process, of a product. However, such systems are inaccurate and unreliable because they fail to consider the time value of money and customer relationships in the long-term. Pursuing lifelong customer relationships is the ultimate goal of many companies, as it brings greater profits and sustainability (Chan *et al.*, 2010). Furthermore, it is more cost-effective to retain existing customers than to acquire new customers (Reinartz and Kumar, 2003; Chan *et al.*, 2010). Using NCLV, rather than profit maximization and transaction-based calculations, to support decision making in NPD in the long term is hence considered in this research. This novel approach should effectively overcome the shortcomings of existing DSSs.

Through the application of Module III, the effectiveness of NPD and marketing strategies can be illustrated in monetary terms. This will also inspire companies to improve profits in the long term by adjusting existing NPD and marketing strategies. Module III, which predicts customer purchasing behavior and estimate NCLV, is novel and can effectively overcome the shortcomings of existing DSSs. The details of sub-model 1 and 2 are discussed below.

5.2.1 Sub-model 1: A Customer Purchasing Behavior Model

Sub-model 1 was developed with the iThink® application, which makes use of system dynamics and is a system modeling and simulating tool. As mentioned in Chapter 2, system dynamics has been extensively employed in strategic planning (Georgantzas, 1996; Lyneis, 2000; Lam *et al.*, 2010) and business decision making (Angerhofer and Angelides, 2000; Chan and Ip, 2008; Ip *et al.*, 2008; Chan *et al.*, 2010). It helps potential users gain insight into the dynamic behaviors of complex systems and make appropriate decisions (Tarek and Stuart, 1991; Lin *et al.*, 1998). Customer purchasing behavior is therefore analyzed in relation to product, customer, and marketing issues in sub-model 1 with the support of the theory of system dynamics.

The model construction layer of sub-model 1 is shown in Figure 5.2. Sub-model 1 includes three groups of customers (potential customers, first-time customers, and active customers), and five customer states (potential, first-time, regular, frequent, and loyal customers). The last three customer states describe the active customers. Various factors influence customer purchasing behavior. Having no experience of using any of the company's products, potential customers initially make a purchase based on "overall product attractiveness" (OPA), "marketing effectiveness" (ME), and "word of mouth" (WOM). The acquisition rate of motivating potential customers to adopt a product initially is determined by Equation (5.1). Existing customers, in contrast, have their own experience and satisfactory level of using the company's products. They are retained by the company based on OPA, WOM, "remarketing effectiveness" (RE), and "overall customer satisfaction" (OCS). The retention rate of upgrading first-time customers to active customers and keeping active customers in the company is determined by Equations (5.2) – (5.5). The factors influencing customer purchasing behavior toward a new product are assumed to be independent of each other. The terms used in sub-model 1 are defined in Table 5.1.

$$AR_t = random\left[C_{1,t} min\left(E_{1,t}, E_{2,t}, E_{3,t}\right), C_{1,t} max\left(E_{1,t}, E_{2,t}, E_{3,t}\right)\right] \tag{5.1}$$

$$RR_t = \sum_{s=2}^{4} RR_{s,t} \tag{5.2}$$

$$RR_{2,t} = random\left[C_{2,t} min\left(E_{1,t}, E_{3,t}, E_{4,t}, E_{5,t}\right), C_{2,t} max\left(E_{1,t}, E_{3,t}, E_{4,t}, E_{5,t}\right)\right] \tag{5.3}$$

$$RR_{3,t} = random\left[C_{3,t} min\left(E_{1,t}, E_{3,t}, E_{4,t}, E_{5,t}\right), C_{3,t} max\left(E_{1,t}, E_{3,t}, E_{4,t}, E_{5,t}\right)\right] \tag{5.4}$$

$$RR_{4,t} = random\left[C_{4,t} min\left(E_{1,t}, E_{4,t}, E_{5,t}\right), C_{4,t} max\left(E_{1,t}, E_{4,t}, E_{5,t}\right)\right] \tag{5.5}$$

where $C_{s,t}$ denotes the number of customers in state s at time t; $s = 1,2,3,4,5$

represent the five customer states of potential, first-time, regular, frequent, and loyal customers, respectively; $E_{n,t}$ refers to the parameters of the five influencing factors of customer purchasing behavior at t; $n = 1,2,3,4,5$ represent "OPA," "ME," "WOM," "RE," and "OCS," respectively; AR_t is the acquisition rate of potential customers at time t; and $RR_{s,t}$ refers to the retention rate of customers in $s = 2,3,4$ at time t moving on to the next state.

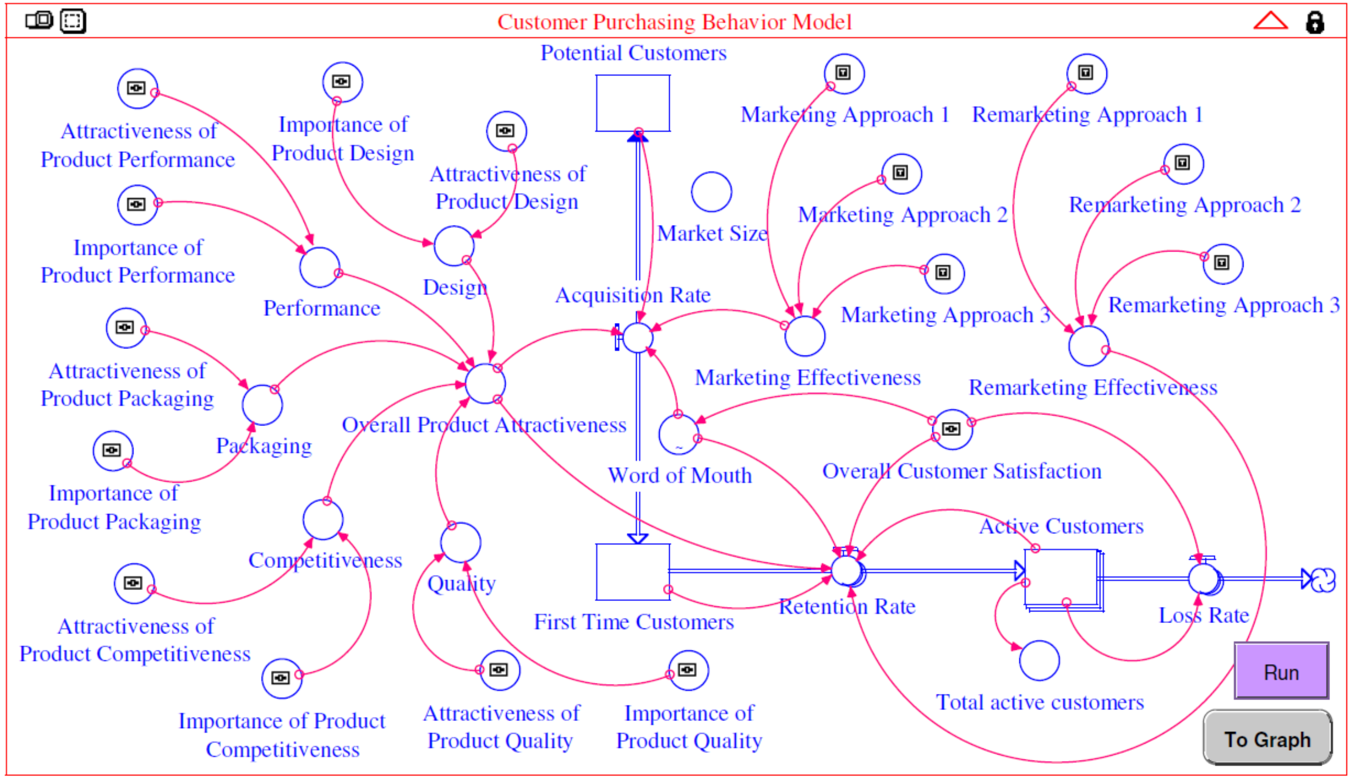


Figure 5.2 Model construction layer of sub-model 1

Table 5.1 Terminology used in sub-model 1

Terms	**Implications**
Potential customers	Target customers who will probably make a purchase
First-time customers	Customers who make an initial purchase of a newly launched product
Active customers	Customers who make repeat purchases of a product and are regular, frequent, or loyal customers
Overall product attractiveness (OPA)	Product design, quality, performance, packaging, and competitiveness, all of which stimulate customers to make purchases
Word of mouth (WOM)	Likelihood of customers sharing their impressions and recommendations of their experience of using the product with others
Overall customer satisfaction (OCS)	Level of customer satisfaction with the product based on personal experience and perceptions of using the product after purchase
Marketing effectiveness (ME)	The effectiveness of a company’s activities to acquire customers from among the public, such as advertisements
Re-marketing effectiveness (RE)	The effectiveness of a company’s activities to retain customers, such as a membership program

(To be continued on the next page)

Table 5.1 Terminology used in sub-model 1

Terms	Implications
Marketing approach (MA)	The marketing strategy adopted by the company, whether an individual marketing campaign or a mixed marketing plan
Re-marketing approach (RA)	The remarketing strategy adopted by the company, either an individual remarketing campaign or a mixed remarketing plan
Attractiveness of product design, quality, performance, packaging, and competitiveness	Scores that the product achieves for design, quality, performance, packaging, and competitiveness as rated by senior management and the NPD team
Importance of product design, quality, performance, packaging, and competitiveness	The importance of customers' preferences in evaluating a product (in terms of product design, quality, performance, packaging, and competitiveness) and deciding whether to purchase it (i.e., the weights of customer requirements)

Sub-model 1 actually takes account of three kinds of influencing factors, which are product, customer, and marketing. This embodies great value to sub-model 1 as existing studies (Moskowitz and Kim, 1997; Herrmann *et al.*, 2000; Khoo *et al.*, 2002; Alexouda, 2005; Fung *et al.*, 2007; Hung *et al.*, 2008; Liu *et al.*, 2008) usually consider only one or two of them. Such discussion can be found in Chapters 1 and 2. The respective influencing factors under these three kinds are discussed below.

A. Product influencing factors

Overall product attractiveness (OPA) is the main stimulus influencing customer cognition and behavior. Customers may evaluate product characteristics based on their own values, beliefs, and past experiences in making a purchase (Solomon *et al.*, 2010). OPA is often assessed in terms of design, quality, performance, packaging, and competitiveness. There are two determinants in each dimension of OPA: the attractiveness of product characteristics according to experts in the company, and the relative importance of different customer requirements, which correspond to product characteristics. Inclusion of both determinants gives a more comprehensive assessment of new product attractiveness.

The attractiveness of product characteristics (in terms of design, quality, performance, packaging, and competitiveness) is a key determinant of OPA and hence customer purchasing behavior. These parameters are determined internally, often by managers and the NPD team. However, customers' preferences are critical to product selection, and thus the relative importance of different customer requirements (including design, quality, performance, packaging, and competitiveness) is another determinant of OPA and customer purchasing behavior. These parameters can be obtained through a customer survey and analyzed using a fuzzy analytic hierarchy process. More specifically, the outputs of Module II introduced in the previous chapter can be used here. OPA is expressed mathematically by Equation (5.6).

$$E_{1,t} = \sum_{f=1}^{5} I_{f,t} A_{f,t} \quad , \tag{5.6}$$

where $f = 1,2,3,4,5$ refers to "design," "quality," "performance," "packaging," and “competitiveness,” respectively; $I_{f,t}$ denotes the parameters of the relative importance of customer requirements in terms of f at t; and $A_{f,t}$ indicates the parameters of product attractiveness in terms of f at t.

B. Customer influencing factors

It is unlikely that customers make purchasing decisions based on product attributes alone. Word of mouth (WOM) and overall customer satisfaction (OCS) are other important factors affecting customer purchasing behavior.

WOM refers to the likelihood of customers sharing with others their impressions and recommendations of their experiences in using a product (Peter and Olson, 2008). Marketing planners generally try to encourage positive WOM communication among customers, as this helps spread customers’ awareness of the introduction of new products (Bayus, 1985). According to the advertising agency JWT Worldwide, over 85% of the top 1,000 marketing companies now use WOM tactics (Wasserman, 2006). According to Arndt (1967), exposure to positive WOM increases the profitability of a purchase, and vice versa. WOM clearly merits attention when making NPD decisions, and is thus regarded as a customer influencing factor in the customer purchasing behavior in sub-model 1.

WOM is closely connected with OCS. It is usual for customers to share their views on a product in their social network based on their level of satisfaction in purchasing and using the product. Satisfied customers share positive WOM, whereas dissatisfied customers engage in negative WOM with others. Many studies have found that WOM and customer satisfaction are positively related, and that both are powerful factors influencing customer purchasing behavior (File and Prince, 1993; Anderson, 1998; Thorsten *et al.*, 2002; Ranaweera and Prabhu, 2003). OCS is thus considered a determinant of WOM. Given the parameter for OCS, the parameter for WOM can be determined through a graphical function (see Figure 5.3), rather than an equation. A positive WOM parameter means that customers share favorable comments, which encourage customers to make a (re)purchase, and vice versa.

OCS, another influencing factor included in sub-model 1, influences the likelihood of customers who engage in WOM, and also encourages first-time customers to purchase and active customers to repurchase. Customers with a higher satisfactory level often have a stronger intention to repurchase and to be loyal. Several studies have found that a higher level of customer satisfaction leads to greater customer loyalty (Anderson and Sullivan, 1993; File and Prince, 1993; Ranaweera and Prabhu, 2003). Thus, in sub-model 1 OCS is considered to influence WOM and also the retention rate. The OCS parameter can be obtained through a customer survey.

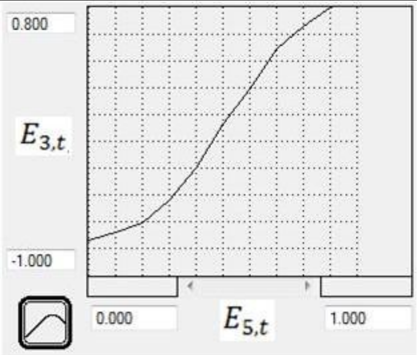
Graphical function	$(\boldsymbol{E_{5,t}}, \boldsymbol{E_{3,t}})$
	$(0, -0.77), (0.1, -0.72),$ $(0.2, -0.65), (0.3, -0.5),$ $(0.4, -0.28), (0.5, 0.01),$ $(0.6, 0.25), (0.7, 0.52),$ $(0.8, 0.67), (0.9, 0.8),$ $(1, 0.88)$

Figure 5.3 Graphical function of WOM versus OCS

C. Marketing influencing factors

It is critical for companies to launch new products successfully to maintain market leadership. Unfortunately, empirical data indicate that one-third to one-half of all new products fail to meet the company's financial and marketing goals (Mansfield and Wagner, 1975; Booz *et al.*, 1982; Cooper and Kleinschmidt, 1993). Poor marketing planning and execution is offered as a possible explanation (Cooper, 1978). Marketing information also influences whether the purchase and use of a product is likely to be rewarding (Peter and Olson, 2008). It is clear that marketing factors and customer purchasing behavior are linked, and are keys to product success. "Marketing effectiveness" (ME) and "remarketing effectiveness" (RE) are thus included in sub-model 1 as marketing factors influencing customer purchasing behavior.

There are many possible forms of (re)marketing campaigns, such as advertising, sales promotions, event sponsoring, and membership programs. Companies often use mixed (re)marketing campaigns as a strategy. In general, marketing campaigns that are effective in conveying messages about a company's product to its target customers are more valuable. However, (re)marketing budgets are often limited, so companies have to consider both (re)marketing budgets and effectiveness when launching new products. Three types of marketing approach (MA) (i.e., MA1, MA2, and MA3) and three types of remarketing approach (RA) (i.e., RA1, RA2, and RA3), defined according to the size of budget (i.e., small, medium, and large, respectively), are available as options in sub-model 1. The relationship between the marketing approaches and ME is expressed in Equations (5.7) and (5.8), and the relationship between the remarketing approaches and RE is stated in Equations (5.9) and (5.10).

$$E_{2,t} = \sum_{x=1}^{3} M_{x,t} X_{x,t} \tag{5.7}$$

$$M_{x,t} = \begin{cases} 1 & , if\ x\ is\ adopted \\ 0 & , otherwise \end{cases} \tag{5.8}$$

$$E_{4,t} = \sum_{y=1}^{3} R_{y,t} Y_{y,t} \tag{5.9}$$

$$R_{y,t} = \begin{cases} 1 & , if\ y\ is\ adopted \\ 0 & , otherwise \end{cases} \tag{5.10}$$

where $M_{x,t}$ represents whether marketing approach x is adopted at time t; $X_{x,t}$ refers to the respective values which show the effectiveness of marketing approach x at time t; $x = 1,2,3$ refers to MA1, MA2, and MA3, respectively; $R_{y,t}$ represents whether remarketing approach y is adopted at time t; $Y_{y,t}$ refers to the respective values which show the effectiveness of remarketing approach y at time t; and $y = 1,2,3$ refer to RA1, RA2, and RA3, respectively.

Based on the aforementioned influencing factors, the number of potential, first-time, and active customers can be predicted by Equations (5.11) – (5.14).

$$C_{1,t} = C_{1,t-dt} + (\sum_{s=3}^{5} LR_{s,t} - AR_{1,t})dt \tag{5.11}$$

$$C_{2,t} = C_{2,t-dt} + (AR_{1,t} - \sum_{s=2}^{4} RR_{s,t})dt \tag{5.12}$$

$$C_{3-5,t} = \sum_{s=3}^{5} C_{s,t-dt} + (\sum_{s=2}^{4} RR_{s,t} - \sum_{s=3}^{5} LR_{s,t})dt \tag{5.13}$$

$$LR_{s,t} = \begin{cases} C_{s,t}Z_{s,1} & , if\ E_{5,t} \geq 0.75 \\ C_{s,t}Z_{s,2} & , if\ E_{5,t} < 0.5 \\ C_{s,t}Z_{s,3} & , otherwise \end{cases} \tag{5.14}$$

where $LR_{s,t}$ indicates the loss rate of customers at $s = 3,4,5$ at time t; $Z_{s,z}$ refers to the fraction of leaving customers at $s = 3,4,5$ that are subject to the conditions $z = 1,2,3$; and $z = 1,2,3$ represent $E_{5,t} \geq 0.75$, $E_{5,t} < 0.5$, and otherwise.

To make sub-model 1 effective when assessing OCS and the influencing factors to support decision making in NPD, the use of slider input devices is applied in sub-model 1. Such devices help decision-makers input and update the parameters for the various factors and determinants more easily. A chained switch is also applied to the set of MA and RA options in Equations (5.8) and (5.10), respectively. Decision-makers can select the desired MA and RA option by simply turning on the option in the respective chain with one-click, which causes the other options to be turned off. The interface layer for sub-model 1 is shown in Figure 5.4. To illustrate the application of this sub-model, a case study is presented later in this chapter.

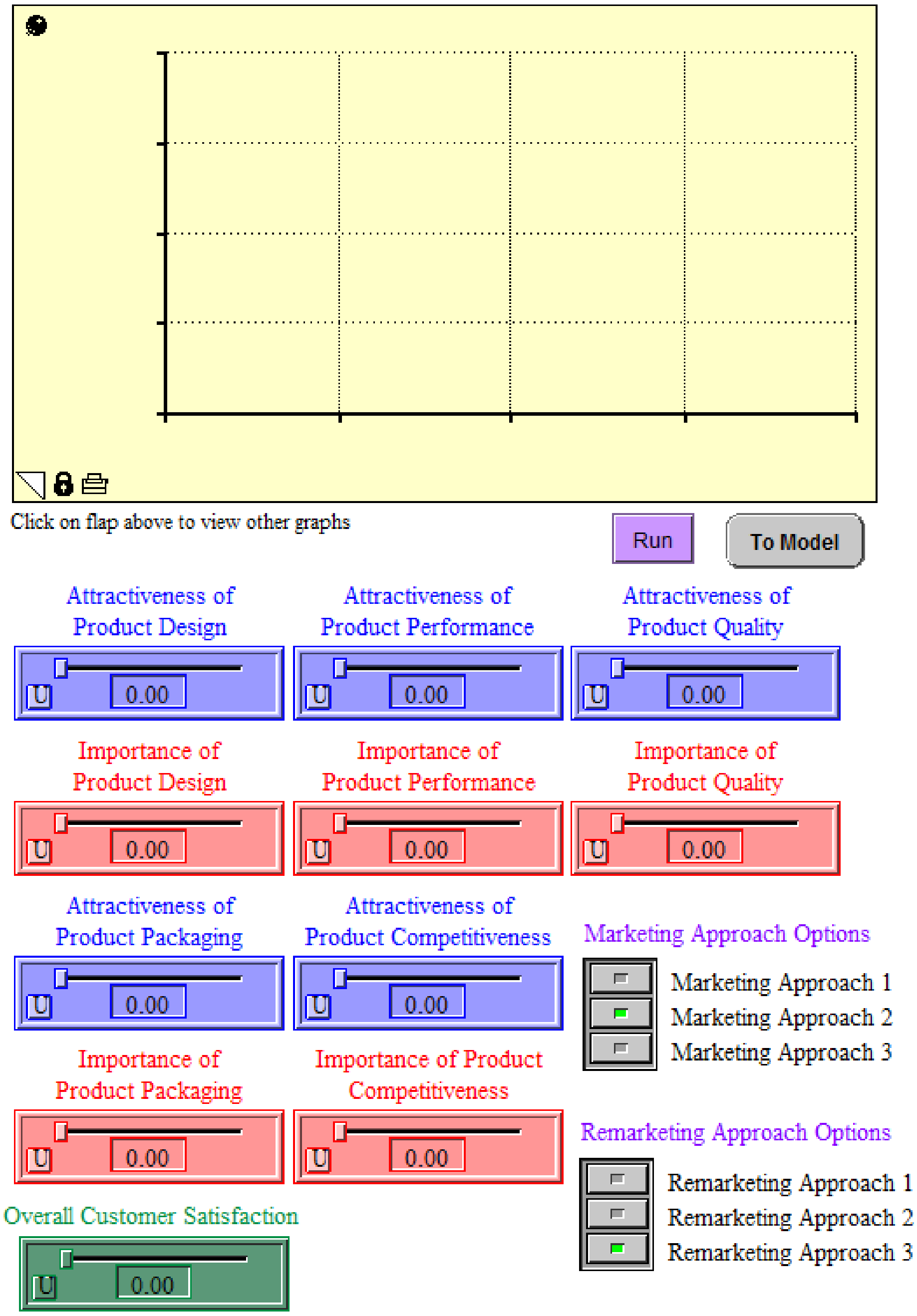


Figure 5.4 Interface layer of sub-model 1

5.2.2 Sub-model 2: A Net Customer Lifetime Value Estimation Model

After the development of sub-model 1, which predicts customer purchasing behavior, sub-model 2 is required to be constructed to estimate the net customer lifetime value

(NCLV). NCLV is defined as the net present values of future profits generated from a customer relationship and a NPD project. It is to determine the economic value of a new product through considering the relationship with a customer in the long term. It is created based on the concept of customer lifetime value (CLV). A consensus has been reached by many scholars that building long-term customer loyalty is crucial to business sustainability (Keh and Lee, 2006; Kumar and Reinartz, 2006; Meyer, 2007). Focusing on lifelong, rather than short-term, customer relationships is a key business strategy for survival in today's competitive marketplace. Considering the time value of money and on-going customer relationships, NCLV, instead of profit maximization and transaction-based calculations, is used as a decisive factor in sub-model 2 to support the approval of NPD projects.

Sub-model 2 applies Markov analysis to estimate NCLV based on the outputs of sub-model 1, which represent the probability of customers switching states over time. In this sub-model, it is supposed that customers can only be in one of the five customer states, i.e., potential, first-time, regular, frequent, and loyal customers. The five customer states in sub-model 2 are corresponding to those in sub-model 1. Hence, customer switching behavior forms a 5×5 probability matrix, P, and the earning vector, E. Furthermore, Equation (5.15) is applied to calculate NCLV.

$$P = \begin{bmatrix} 1-p_1 & p_1 & 0 & 0 & 0 \\ 1-p_2 & 0 & p_2 & 0 & 0 \\ 1-p_3 & 0 & 0 & p_3 & 0 \\ 1-p_4 & 0 & 0 & 0 & p_4 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix};\ E = \begin{bmatrix} RP-MC \\ -RC \\ -RC \\ -RC \\ 0 \end{bmatrix}$$

$$NCLV = \sum_{s=1}^{5} \sum_{t=0}^{T} P^t\, E(1+D)^{-t} - CS \tag{5.15}$$

where p_1 is the probability of customers switching from the current state (i.e., $s = 1$) to the next state (i.e., $s = 2$), which is also applied to explain p_2, p_3, p_4; RP

refers to the retail price of a product; MC is the marketing cost; RC is the remarketing cost; CS is the cost of goods sold; P^t is the switching probability at time t; and D is the discount rate. As mentioned, the outputs of sub-model 1 serve as the inputs of sub-model 2. Hence, p_1 is equivalent to $AR_{t=0}$ divided by the initial number of potential customers; p_2 equals $RR_{2,t=1}$ divided by $C_{2,t=0}$; p_3 equals $RR_{3,t=2}$ divided by $C_{3,t=1}$; and p_4 is equal to $RR_{4,t=3}$ divided by $C_{4,t=2}$.

5.3 Case Study

To illustrate and verify the application of Module III of the proposed iDSS, a case study is presented in this section. It further highlights the effectiveness of Module III. A brief description of the data used in the case study is given first, followed by the case study.

Data

Data on product attributes, customer satisfaction and behavior, marketing plans and significance, and financial information from the database of the case company are used in this case study. Seven power tools (Products A-G) in the same product family are randomly chosen as representative samples. These seven products are developed from the ideas which were selected with go decisions in Module I. Due to confidentiality, all of the actual data, excluding retail prices and discount rate, are concealed, but their parameters are displayed in Table 5.2. The cost of goods sold as well as the marketing and remarketing costs are neither displayed nor converted to parameters due to data confidentiality. The data are applied to Module III for simulation, and then for calculating NCLV. To verify Module III, Equation (5.16) is then used to calculate the net present value (NPV), which is compared to NCLV. NPV is the sum of the present values of future cash flows, and is an indicator that helps companies decide whether an investment should be made. Module III has no involvement in the NPV calculation. NPV is generally used by companies, including the case company, to formulate business strategies regarding NPD (Haley and Goldberg, 1995; Kalish, 1985; Kalish *et al.*, 1995; Pennings and Lint, 1997), project management and scheduling (Reyck *et al.*, 2008; Yang *et al.*, 1993), production (Grubbstrom, 1998), and marketing (Cook, 1985; Srivastava *et al.*, 1999).

$$NPV = \sum_{t=0}(RP_t - MC_t)(1+D)^{-t} + \sum_{t=1}^{T}(RP_t - RC_t)(1+D)^{-t} - CS \qquad (5.16)$$

Indeed, the parameters of Products A-G regarding the attractiveness of product performance, product quality, product design, product packaging, and product competitiveness are defined by experts based on their experience and according to the principle of product attractiveness assessment. The scorecard (see Table 5.3) which assesses product attractiveness is designed based on the four-level hierarchy (see Figure 4.3) created in Module II and the experience and intuition of experts from the case company. It is helpful in converting qualitative terms, regarding product specifications, into quantitative values, thus allowing managers to easily make use of such values as parameters for the operation of Module III. Interviews were conducted to collect information for this case study. Since the product characteristics in this assessment scorecard are corresponding to those in the questionnaire of the customer survey adopted in Module II, it is practical for companies, including the case company, to collect both experts' and customers' judgments on the same issue. Their opinions are then input into Module III to assess the overall product attractiveness. The opinions of experts and customers are generally in different languages. This explains why the assessment scorecard evaluating product attractiveness and the questionnaire used in the customer survey are established. The former is needed to collect experts' judgments while the latter is to collect the voice of customers. Both are useful to quantify experts' and customers' opinions.

Table 5.2 Parameters input into Module III of the proposed iDSS

Product	**A**	**B**	**C**	**D**	**E**	**F**	**G**
Parameters for Sub-model 1:							
Attractiveness of Product Performance	0.375	0.375	0.25	0	0.375	0.875	1
Attractiveness of Product Quality	0.4583	0.4583	0.5417	0.4583	0.7083	0.4583	0.4583
Attractiveness of Product Design	0.5625	0.5	0.4688	0.625	0.5313	0.4375	0.3125
Attractiveness of Product Packaging	1	1	0.75	0.5	0.75	0.75	0.75
Attractiveness of Product Competitiveness	0.5	0.5	0.5	0.5833	0.5	0.5	0.5
Marketing Approach Option	2	2	1	1	2	3	3
Re-marketing Approach Option	3	2	2	2	1	2	2
Importance of Product Performance	0.6867	0.6867	0.6867	0.6867	0.6867	0.6867	0.6867
Importance of Product Quality	0.3038	0.3038	0.3038	0.3038	0.3038	0.3038	0.3038
Importance of Product Design	0.1514	0.1514	0.1514	0.1514	0.1514	0.1514	0.1514
Importance of Product Packaging	0.1246	0.1246	0.1246	0.1246	0.1246	0.1246	0.1246
Importance of Product Competitiveness	0.1515	0.1515	0.1515	0.1515	0.1515	0.1515	0.1515
Overall Customer Satisfaction	0.83	0.83	0.83	0.83	0.83	0.83	0.83
Parameters for Sub-model 2:							
Retail Price (USD)	$336	$361	$149	$139	$299	$349	$339
Discount Rate	10.9%	10.9%	10.9%	10.9%	10.9%	10.9%	10.9%

Table 5.3 Product attractiveness assessment scorecard

Dimensions	**Criteria**	**Attributes**	**Measurement**	**0**	**0.25**	**0.5**	**0.75**	**1**
Performance	Robustness	The ability to endure tough applications	Maximum torque (in-lbs)	<350	350-449	450-549	550-649	>=650
	Efficiency	To complete applications (e.g. drilling and fastening) quickly and easily	High speed (no load) (rpm)	<1301	1301-1400	1401-1600	1601-1700	>1700

(To be continued on the next page)

Table 5.3 Product attractiveness assessment scorecard

Dimensions	**Criteria**	**Attributes**	**Measurement**	**0**	**0.25**	**0.5**	**0.75**	**1**
Quality	Durability	The durability of surviving from drops	Endures 6 feet repeated drop durability	<5times	5times	6times	7times	>7times
	Reliability	Lower risk to users (e.g. bits do not fail out, and chucks do not require frequent retightening due to bit slippage)	Chunks with increased bit grip designs, i.e., self tightening and axial locking sleeve	No				Yes
		Long-lasting battery	Battery capacity (Ahr)	≦2		2		≧3
			Charging time (mins)	>60	50-60	40-50	30-40	<30

(To be continued on the next page)

Table 5.4 Product attractiveness assessment scorecard

Dimensions	**Criteria**	**Attributes**	**Measurement**	**0**	**0.25**	**0.5**	**0.75**	**1**
Design	Versatility	Variable speed settings	Number of speed transmissions	1		2		3
		Multiple chunk and bit fittings	Multiple chunk and bit fittings	No				Yes
	Weight and size	Light weight	Weight (with battery) (lbs)	>5	4.6-5	4.1-4.5	3.5-4	<3.5
		Compact size	Overall length (inches)	>8.9	8.5-8.9	8-8.4	7.5-7.9	<7.5
	Ergonomics	Comfortable handle	Cushioned, soft-grip trigger	No				Yes
		Well-balanced	Reversible battery	No				Yes
	Convenience	Built-in LED lights	LED illumination	No				Yes
		One handed bit insertion	One handed bit insertion	No				Yes

(To be continued on the next page)

Table 5.5 Product attractiveness assessment scorecard

Dimensions	**Criteria**	**Attributes**	**Measurement**	**0**	**0.25**	**0.5**	**0.75**	**1**
Packaging	Warranty	Longer warranty period	Warranty (years)	<1	1	2	3	>3
	Carrying case	To provide protection	Provides protection	No				Yes
		To provide storage for tool and bits	On-board bit storage	No				Yes
Competitiveness	Price	Reasonable price	Percentage by which the retail price of the company is more or less than that of competitors	>10% (more than)	6-10% (more than)	5% (more or less than)	6-10% (less than)	>10% (less than)
	Time	Quick response to market in launching new products	Development time (months)	>24	19-24	13-18	6-12	<6
	Brand	Well-known brand	Market share of brand	<5%	5-14%	15-34%	35-45%	>45%

Discussion of the Results of Sub-model 1

By running sub-model 1 with the parameters shown in Table 5.2, customer behavior toward Products A-G is predicted. The customer switching probabilities, i.e., p_1, p_2, p_3, and p_4, are estimated and presented in Table 5.4. The migration of customers from the state of potential customers to that of active customers is shown in Figure 5.5.

Table 5.4 shows that customer switching probabilities vary with products and time. Customers often behave in a different way toward products with specific attributes under the influence of (re)marketing campaigns. With reference to Products F and G, the company invested in the same kind of (re)marketing campaigns to introduce them into the market. However, the customer switching probabilities of Products F and G differ, and show no common trend. This demonstrates that customer purchasing behavior is dynamic. Customer purchasing behavior depends not only on marketing influencing factors, but also product and customer influencing factors.

Although the results in Table 5.4 show no specific trend in customer switching probabilities, the results in Figure 5.5 suggest that there is a pattern to customer purchasing behavior toward Products A-G. The movement of potential and active customers follows an S-shaped curve, whereas that of first-time customers follows a bell-shaped curve. Figure 5.5 infers that the company is unlikely to acquire all target customers. However, it is most important to motivate first-time customers to become active customers and retain active customers in the long term. The cost of acquiring new customers exceeds the cost of retaining existing customers by a substantial margin (Dyche, 2002). Customer loyalty is thus important for the company to sustain growth and maximize profits.

Taking Product E in Figure 5.5 as an example, the number of first-time customers continues to grow in the first 1.75 years but starts to decline thereafter. The figure also demonstrates that potential customers are active in purchasing and then switch to the state of first-time customers during the first 1.75 years due to their initial purchase. It is thus more effective for the company to promote the product during this period to capture more value from customers. Mass marketing campaigns, such as advertising, publicity, trade shows and events, mass media, and online marketing are likely to be most suitable under this circumstance. After acquiring customers, greater emphasis should be placed on customer retention. After Product E had been introduced for 1.75 years, first-time and active customers should be remarketed, for this is essential to achieve market sustainability. Membership programs, face-to-face marketing activities, and privilege offers are likely to be particularly effective after the first 1.75 years and up to the fourth year.

Figure 5.5 further shows that the number of active customers purchasing Products A-G reaches a peak and remains steady thereafter. This implies that the target customer segment is saturated and the products launched have already fulfilled customer needs. In this circumstance, customers are neither interested in the products nor intend to purchase them further. Knowing the customer migration (see Figure 5.5), the company can anticipate when a new product should be launched to prolong the relationships with its customers. For example, the number of customers purchasing Product B in the target segment approaches the maximum after 4.375 years after product introduction (see Figure 5.5). This is then the optimal time for the case company to launch another new product to expand its market reach and further satisfy customer needs.

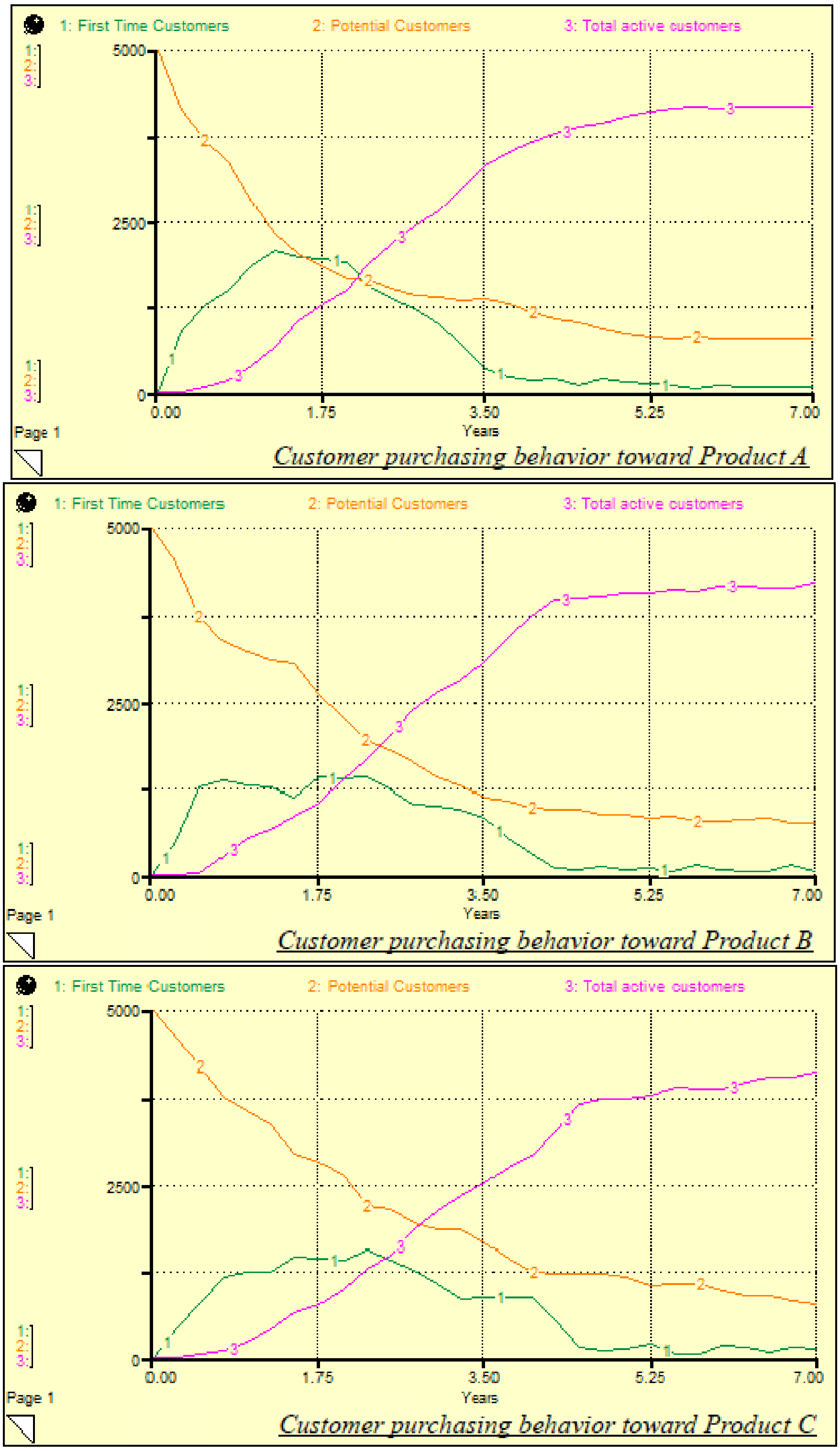


Figure 5.5(a) Customer purchasing behavior toward the seven power tools

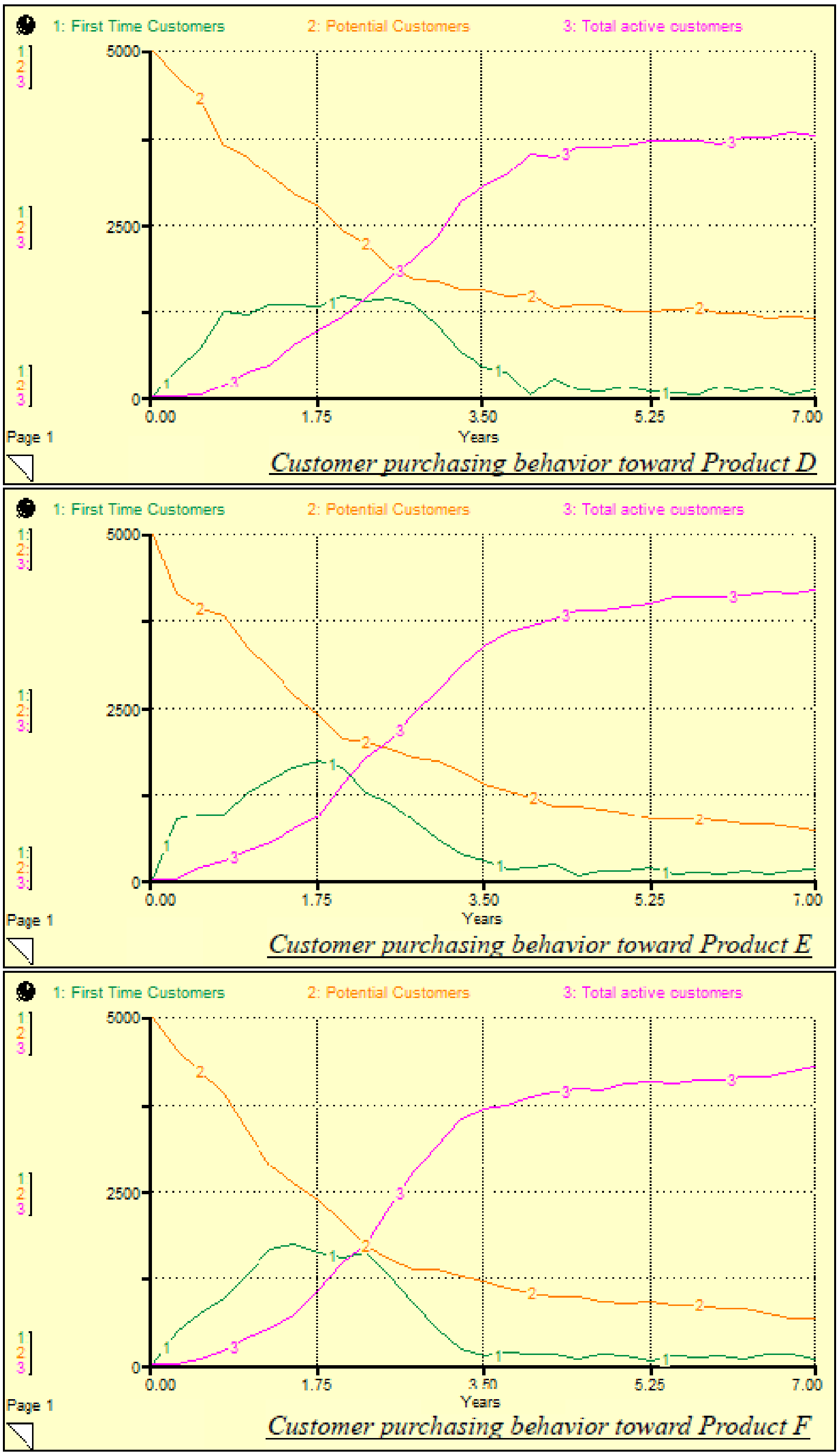


Figure 5.5(b) Customer purchasing behavior toward the seven power tools

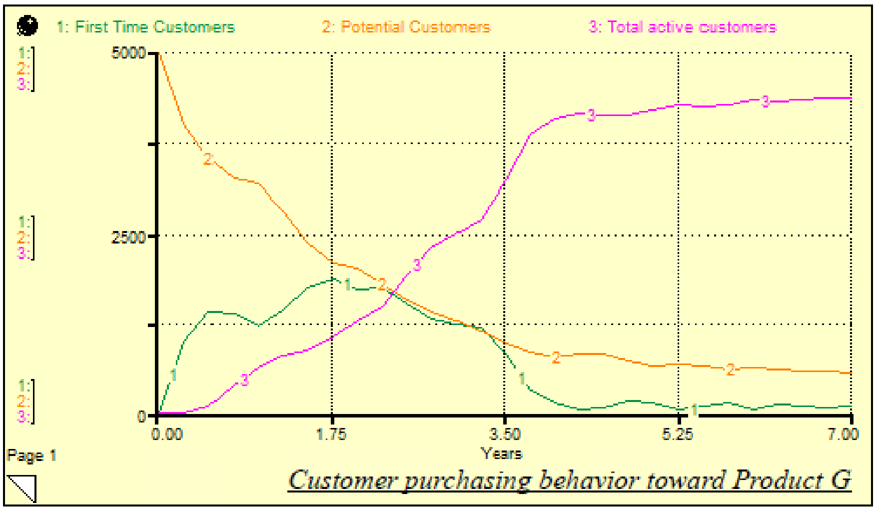


Figure 5.5(c) Customer purchasing behavior toward the seven power tools

Discussion of the Results of Sub-model 2

To predict the NCLV for Products A-G, the probabilities that result from sub-model 1 are used as inputs into the probability matrix *P* in sub-model 2. The predicted probabilities are combined with information on retail price, marketing cost, remarketing cost, and discount rate to determine the NCLV for Products A-G over four periods (see Table 5.4) in sub-model 2. To verify Module III, the NPV for each product is estimated using Equation (5.16). The results of the NPVs and the difference between the NPV and NCLV for each product are shown in Table 5.5.

After prioritizing the NCLV for Products A-G in Table 5.4, it becomes clear that in a long-term customer relationship Product B is the most profitable product (NCLV=US$997.7) and Product D is the least profitable one (NCLV=US$333.5). The results in Table 5.4 and Figure 5. show that there is no obvious evidence to indicate which influencing factor drives Product B to be relatively more favorable, or to explain why Product B is the most profitable and Product D the least. This finding implies that customer purchasing behavior is based on a combination of the various influencing factors, rather than any one factor alone.

It is not necessarily the case that a product which initially has a higher probability of motivating potential customers to purchase is the most profitable in the long term, and vice versa. For example, the probability of potential customers buying Product A is 0.44 (see Table 5.4), which is the highest among the various alternatives. However, the NCLV for Product A is US$866.8 (see Table 5.4), which ranks third, showing that it is not the most profitable product. This suggests that the case company should place emphasis not only on customer acquisition but also on customer retention and loyalty. The amount of profit derived from the customer relationship is attributable to the degree of customer loyalty and the length of the customer relationship, rather than the rate of customer acquisition. Clearly, securing lifelong customer relationships is the key to product success and greater profits for the company.

Table 5.5 demonstrates that the differences between the NPVs and NCLVs range from 1.19% to 4.44%, which are considered minor and acceptable. This further implies that Module III is reliable at a 95% significance level. The NCLVs for Products A-G are arranged in descending order. However, the order of the NCLVs for Products A-G differs slightly from that of the NPVs. This may affect how decision-makers sift through the product alternatives to find the relatively more favorable products that will generate greater profits. To further verify the precision of this module and explore this issue, additional data from the case company regarding the profitability of Products A-G were acquired (see Table 5.5). The information shows that the order of Products A-G, in terms of profitability, is identical to that of the NCLVs. This further confirms that Module III is useful for precisely and accurately determining the NCLV and prioritizing products.

Compared with the NCLVs, the NPVs are inaccurate and overestimated. This is possibly because the calculation fails to consider customer purchasing behavior specifically in terms of the customer switching probability. In contrast, the insight into customer purchasing behavior obtained from the NCLVs could play an important part in helping companies make appropriate decisions on NPD. This further embodies great value to Module III.

Table 5.4 Results of Module III

Product	**A**	**B**	**C**	**D**	**E**	**F**	**G**
Outputs from Sub-model 1:							
p_1	0.44	0.36	0.29	0.31	0.33	0.33	0.37
p_2	0.39	0.44	0.48	0.5	0.49	0.64	0.38
p_3	0.48	0.56	0.68	0.68	0.53	0.76	0.53
p_4	0.43	0.62	0.36	0.34	0.17	0.04	0.48
Outputs from Sub-model 2:							
NCLV (USD)	$866.8	$997.7	$370.5	$333.5	$690.9	$868.6	$837.2
NCLV in order	3	1	6	7	5	2	4

Table 5.5 Comparison of NCLVs with NPVs

Product	A	B	C	D	E	F	G
NCLV (USD)	$866.8	$997.7	$370.5	$333.5	$690.9	$868.6	$837.2
NPV (USD)	$889.6	$1013.3	$378.7	$349.0	$713.7	$879.1	$871.8
NPV in order	2	1	6	7	5	3	4
Difference between NCLV and NPV	2.56%	1.54%	2.17%	4.44%	3.19%	1.19%	3.97%
Profitability in order	3	1	6	7	5	2	4

Findings of the Dynamic Decision Model

It is challenging for companies to respond to customer needs in today's competitive marketplace due to rapid technological advancement and volatile demand. Customer purchasing behavior is dynamic. Simply observing historical customer purchasing behavior is ineffective to support NPD decisions. Furthermore, decisions on NPD are complicated, and require knowledge about the products, its customers, and marketing; communication between multiple departments are required. Sub-model 1 of Module III of the proposed iDSS is a dynamic feedback system which is capable of helping a company integrate product, customer, and marketing information through simulation, so as to analyze and predict customer purchasing behavior. Sub-model 1 is designed to enable managers to input and update parameters, making decisions in a fast and efficient manner. Gaining insight into customer purchasing behavior, a company can make future plans for NPD and formulate proper marketing strategies. Sub-model 1 offers significant support for decisions on NPD and CRM.

In the literature, profit maximization is normally used as the basis for the selection of new products among alternatives. Profit is generally calculated in the short term using historical or current data, which may be inaccurate or out of date. This may cause a company to introduce less attractive and even unfavorable products into the market, which will negatively affect its market share and profitability. To take long-term profit into account, NCLV is estimated in sub-model 2 by making use of the outputs from sub-model 1. NCLV is useful for distinguishing the best product and prioritizing products in terms of their long-term profitability. This allows a company to select more favorable and attractive products to launch so as to generate greater profits in the long term.

Overall, Module III is significant and valuable. It helps companies (a) respond to customer needs by designing and developing new products that are market-driven; (b) stimulate customers to make (re)purchases by formulating proper marketing strategies; and (c) sustain business growth and profitability through the selection and launch of worthy products. Companies can easily evaluate different marketing approaches and NPD projects using Module III through altering the input values of the sub-models. This will help them forecast the long-term return on investment of tentative business strategies and identify improvements to NPD projects and (re)marketing approaches.

5.4 Chapter Summary

Module III of the proposed iDSS is developed to focus on the modeling of customer purchasing behavior and the estimation of NCLV. Module III consists of a customer purchasing behavior model (sub-model 1) and an NCLV estimation model (sub-model 2). The structure and formulation of these two sub-models have been described. The applicability of Module III is verified by applying it to seven products that are power tools from the case company. Module III includes three kinds of influencing factors, namely product, customer, and marketing. This resolves the problem stated in Problem Statement C in Chapter 1. There are 10 determinants regarding product influencing factors among which five are from the perspective of experts, and another five are from the perspective of customers. Customer influencing factors are in terms of word of mouth and overall customer satisfaction. Marketing influencing factors include (re)marketing effectiveness, and (re)marketing approaches. Customer purchasing probabilities can be determined by investigating customer purchasing behavior, and its results are shown in Table 5.4. Taking account of customer satisfaction and customer purchasing behavior, Module III further deals with the issue discussed in Problem Statement D in Chapter 1. The NCLVs for the seven power tools are determined and the results are exhibited in Table 5.5. It shows that Product B is the best product that brings the greater long-term profits to the case company while Product D brings the least. As the actual profitability of the seven products and the NCLVs are in the same order, this confirms that the estimation of NCLV is convincing and reliable. By accurately determining the value that customers bring to the company in terms of NCLV, the problem stated in Problem Statement E in Chapter 1 is resolved.

In addition, the findings of Module III have been explored, and it is concluded that Module III predicts the customer switching probability and determines NCLV for new products in order to offer effective decision support. Module III is also useful in distinguishing the best product and prioritizing products in terms of their long-term profitability. Providing a detailed evaluation of NPD projects, Module III helps companies select and approve competitive NPD projects for further investment. Competitive NPD and CRM strategies can be formulated by providing Module III with different scenarios for testing. It is found that Module III is able to aid companies in making more sensible decisions and achieving greater success in NPD and business growth.

CHAPTER 6 CONCLUSIONS AND FUTURE RESEARCH

6.1 Research Summary and Conclusions

Successful new product development (NPD) is a competitive weapon and is important to business success. Through delivering value to customers through new products, companies should satisfy customer requirements and establish relationships with customers so as to generate profits. NPD and customer satisfaction are associated. However, NPD is a challenging task for many companies. Ineffective decision making on NPD could cause companies to invest in unsuccessful or worthless new product ideas and NPD projects, which lead to failure of NPD. This results in a waste of resources and time, loss of money and market share, or even cessation of business. With reference to the literature, the following five problems, which lead to the failure of making effective decisions, are identified.

- Unable to make appropriate screening (either a go or kill) decisions for all new product ideas;
- Not truly listen to the voice of customers in market-driven NPD;
- Fail to integrate all key influencing factors into a decision support system (DSS) for NPD;
- Not take customer satisfaction and customer purchasing behavior into account; and
- Calculate the value that customers bring to a company inaccurately.

Providing managers with a new and comprehensive decision support system (DSS) to make sensible and reliable NPD decisions is therefore required. Such DSS is essential to evaluate, select, and approve successful and attractive new product ideas and NPD projects for further development at the front end of the NPD process before huge investment is made. Eliminating worthless new product ideas can enable companies to pay particular attention to new product ideas and NPD projects that are customer-focused and worthy of investment. This will enhance NPD, making companies excel in the market and sustain business growth.

In order to respond to the need of a new and innovative DSS, an integrated decision support system (iDSS) composing three core modules for NPD, with particular concern on customer satisfaction, is proposed. The three modules of the proposed iDSS are then verified through case studies of a power tool company in this research. These form the key objectives of this research mentioned in Chapter 1. The iDSS is designed to support NPD decision making based on the perspectives of both experts and customers. Taking account of product-related, customer-related, and marketing-related factors, the iDSS ultimately provides a financial estimate, in terms of net customer lifetime value (NCLV), enabling managers to decide on which NPD investment is to be made. The proposed iDSS is useful at the front end of the NPD process. It consists of three modules, namely Module I: an idea screening decision model, Module II: a customer perception model, and Module III: a dynamic decision model.

A mixed methodology and various decision-making techniques are employed in this research to develop the iDSS. Module I emphasizes the perspective of experts. An evaluation scorecard and a hidden Markov model (HMM) are developed and integrated in Module I, in which managers can convert linguistic judgments to quantifiable and comparable data, and determine the success probability of all of the new product ideas. Selected ideas will be further investigated, defined as NPD projects, and moved to the next stage of the NPD process for the sake of further development. Module II, which centers on the perspective of customers, is developed through a customer survey and a fuzzy analytic hierarchy process (FAHP) algorithm. The relative importance of product characteristics, which are corresponding to customer requirements, is weighed and prioritized from the customers' perspective. This will inspire managers to design and develop customer-focused new products which fulfill customers' actual needs and maximize customer satisfaction. Only the new product ideas selected through Module I will be further evaluated in Module III, for those discarded ideas are unworthy of further attention. Module III takes account of the relative importance weights of customer requirements, which are the results of Module II. iThink®, a system dynamics application, and Markov analysis are employed in Module III. There are two sub-models in Module III, namely the customer purchasing behavior model (sub-model 1), and the NCLV estimation model (sub-model 2). In sub-model 1, customer purchasing behavior is modeled by considering all key influencing factors that are product-related, customer-related, and marketing-related. Both experts' and customers' judgments are involved in sub-model 1, which predicts customer purchasing probabilities of particular products. In sub-model 2, NCLV is estimated by making use of the outputs from sub-model 1. This helps managers evaluate NPD projects in monetary terms and approve profitable customer-desired projects to be launched in the long term.

To conclude, the key objectives of this research given in Chapter 1 are achieved. First, the framework of the proposed iDSS for NPD has been established in this research (see Figure 1.4). It consists of three core modules, which are connected and serve specific purposes. Second, the three modules have been devised to tackle the problems mentioned in Problem Statements A-E given in Chapter 1. Module I can facilitate decision-makers to make appropriate screening decisions for all new products ideas. It suggests that go decisions should be made when the success probability of new product ideas lie in the interval [0.53, 1]. Module II enables companies to listen to the voice of customers and recognize customer needs by analyzing the results of a customer survey using an integrated approach of the geometric mean method and FAHP algorithm. It is found that the durability, efficiency, and robustness of power tools are the top three important characteristics that customers desire. Module III considers not only a range of product, marketing, and customer influencing factors but also customer satisfaction and customer purchasing behavior, making it practical to calculate the value that customers bring to a company (i.e. NCLV) accurately. It is found that NPD projects with higher NCLVs are more profitable and should be launched. Third, the proposed iDSS is confirmed to be convincing after each module of the iDSS is demonstrated and validated through a case study in the power tool industry. The iDSS can aid decision-makers in effectively deciding which ideas and products are worth further investment and generate greater profits in the long term.

The overall benefit of the application of iDSS is showed in Table 6.1. The iDSS serves as an effective and systematic tool for managers to assess and approve new product ideas and NPD projects. Additionally, it provides managers with useful and systematic information, such as scorecards that can assess new product ideas and project attractiveness, the evaluation results of new products, as well as the customer behavior. This helps improve the consistency of the decision-making process of NPD. With the support of the iDSS, communication errors and conflicts among personnel from multiple functions can thus be minimized. The iDSS facilitates the decision-making process through effective analysis of new products, and thus reduces the overall development time of new products. With reference to Table 6.1, the development time in phase 1 (Define) and phase 2 (Design) shown in Figure 1.1 has been shortened by 9.4% and 3.2%, respectively. Shortening NPD time can essentially help the company quickly respond to and satisfy customer needs. The company can even earn monopoly profits if it is the first mover. More importantly, the iDSS helps companies improve the success rate of NPD by further developing and launching new products, which better fit customer requirements and can be successfully manufactured by companies with the support of resources and know-how. According to the project successful rate index of the case company, the percentage of unsuccessful project has been reduced by 2.5% and that of the project on hold has been reduced by 10.4% after applying the iDSS (see Table 6.1). Improving the success rate helps the company deliver value to customers by offering customer-focused new products, which could maximize customer satisfaction. This demonstrates that the iDSS is useful for risk management and decision making in NPD. Overall, as mentioned by the NPD director of the case company, “the iDSS improves efficiency in the NPD decision-making process and the quality of decision making. This will enhance our ability to generate value-added new products and drive real expansion of the global customer base.” This confirms that the iDSS is meaningful in improving the effectiveness of NPD decision making in response to customer needs, thus achieving the research aim.

Table 6.1 Overall benefit of the application of iDSS

Performance Measurement	**Without the iDSS**	**With the iDSS**	**% Change**
Project Successful Rate Index:*			
Unsuccessful project	2 (2.5%)	0 (0%)	-2.5%
Project on-hold	10 (12.5%)	2 (2.1%)	-10.4%
Man-hour Analysis#:			
Development time in phase 1 (Define) (see Figure 1.1)	235 man-hours	213 man-hours	-9.4%
Development time in phase 2 (Design) (see Figure 1.1)	2600 man-hours	2516 man-hours	-3.2%

*Data related to unsuccessful projects and projects on-hold was provided by the NPD department of the company.
#Data related to the development time in phase 1 and 2 was given by the engineering department of the company.
Remarks: The details of the raw data were not given as they were aggregated and collected through the departmental managers.

6.2 Contributions

A successful NPD is a competitive weapon which helps companies deliver customer values so as to defeat rivals and to dominate in the market. Satisfying customers through new products is crucial to business success. The current practices of NPD are however deficient and unsophisticated, leading to a high failure rate. The problems concerning this issue have been identified in Problem Statements A-E mentioned in Chapter 1. This research attempts to establish the iDSS in response to the need of a new and comprehensive DSS for NPD with a consideration of customer satisfaction. The framework of the iDSS has been developed and validated in this research. The proposed iDSS is unique and capable of addressing the problems. This research thus contributes to enrich the literature as well as to contribute to the industry.

This research indeed makes efforts to consolidate the literature and offer the industry a solid DSS for NPD with a consideration of customer satisfaction through performing these tasks:

In Module I,

(i) Identifying six critical criteria for evaluating new product ideas, including customer needs, market strength, technical competency, manufacturability, logistics and distribution strength, as well as the consideration of risk buy;

(ii) Developing a scorecard for idea evaluation that aids in converting linguistic terms, which are qualitative and incomparable, into quantifiable data. This makes the judgments more concrete and streamlines the decision-making process in NPD that involves experts from multiple disciplines and departments; and

(iii) Building an HMM to determine the probability of success and the optimal cut-off value for making either a go or kill decision on each idea. In the case study, go decisions should be made when the success probability of new product ideas lie in the interval [0.53, 1]. On the other hand, past studies can only differentiate the single best idea among alternatives and provide no support to make decisions toward the rest.

In Module II,

(i) Establishing a four-level hierarchy of product characteristics, which covers 19 product attributes, that links the understanding of experts and customers;

(ii) Surveying customers' perceptions regarding their requirements, which correspond to product characteristics;

(iii) Demonstrating how to synthesize and analyze customer opinions through incorporating the geometric mean method and FAHP. This guides companies to hear the voice of customers and analyze their actual needs; and

(iv) Determining the relative importance and prioritization of product characteristics from the customers’ perspective to recognize customers’ actual needs. In the case study, the durability (the durability of surviving from drops), efficiency (to complete applications quickly and easily), and robustness (the ability to endure tough applications) of power tools are the top three important characteristics, which correspond to customer requirements, that the company should emphasize.

In Module III,

(i) With regard to customer purchasing behavior, identifying a range of product, marketing, and customer influencing factors, including but not limited to product attractiveness, marketing effectiveness, customer satisfaction, and word of mouth;

(ii) Modeling customer purchasing behavior through the system dynamics approach; and

(iii) Creating an equation to calculate NCLV in support of comparing, selecting, and approving worthy projects to be further developed for mass production and product launch. This supports companies to build relationships with customers in the long term for greater profits. Through the case study, it is found that NPD projects with higher NCLV are more profitable, as they satisfy customers and generate greater profits in the long term, and thus worth further investment.

Being a scientific way to assess and approve new product ideas and NPD projects, the established iDSS makes further contributions on managing NPD systematically and improving NPD. These contributions are beneficial to the industry as follows:
The iDSS can inspire designers and engineers to discover and generate new ideas of customer-focused products, as well as to improve current products, for the sake of maximizing customer satisfaction. This is because the iDSS does integrate customers' judgments to support decision making in NPD so that designers and engineers can better develop new products that reach higher level of customer satisfaction. Furthermore, sub-model 1: a customer purchasing behavior model in Module III in particular provides a systematic platform that allows managers to test different NPD strategies in terms of different product specifications by simply changing the parameters in different scenarios.

It also supports marketing personnel to formulate strategic marketing plans and campaigns to a greater extent of effectiveness. Since NPD is a multi-disciplinary activity and it is often associated with the marketing function, the iDSS considers not only product-related and customer-related factors, but also marketing-related factors. This enables marketing personnel to test various marketing strategies toward particular new products so as to formulate the best-fit marketing plans and maximize the effectiveness of marketing.

In addition, it facilitates the decision-making process in NPD. The NPD decision-making process involves massive amount of information; experts from different departments also speak different languages and have diverse backgrounds and responsibilities. Because of these it is often difficult to communicate and reach a consensus about decision making in NPD. The iDSS is capable of converting all linguistic and qualitative terms into quantitative and comparable data. This will improve communication and reduce conflicts among experts, as well as harmonize all experts' judgments when making decisions. The iDSS is also designed to serve as a systematic approach to integrate and analyze such information to support decision making. This facilitates the information flow and collaboration among multiple business functions, including R&D, quality, manufacturing, marketing, financial, and engineering.

The iDSS further aids managers in evaluating NPD projects from the perspectives of both experts and customers, instead of only and heavily relying on experts' experience and intuition. More importantly, the measures with regard to product attributes that are judged by experts and customers are corresponding and consistent. This helps managers further approve and invest in NPD projects that better fit customer needs based on the voice of customers and users, not only on experts' judgments about what customers need and what kinds of products should be developed and launched. Apart from this, both internal and external factors are also considered when evaluating NPD projects. Internal factors are related to the company's internal competency while external factors are related to the customer requirements and demands. These factors are important to the success of NPD. Companies can make use of the iDSS to analyze these factors. This prevents companies from investing in any project that cannot fulfill customers' actual needs and is out of the company's know-how and capacity, resulting in NPD failure. Thus, companies can concentrate efforts and resources on favorable projects, and eliminate a waste of investment in worthless projects. More importantly, the iDSS supports managers to decide and approve if the NPD projects should be further invested to launch in the long term. Such decisions are based on the estimation of NCLV that is in monetary terms and considers on-going customer relationships. This enables managers to deliver new products to fulfill and satisfy customer needs, and more importantly, to build long-term customer relationships. Launching worthy new products to satisfy customers helps companies gain sustainable competitive advantages. This is particularly beneficial to establishing customer loyalty, maximizing the success of NPD, and sustaining business growth.

6.3 Limitations

The proposed iDSS makes great contributions but there are also some limitations. One limitation is that a relatively low response rate of 68% has resulted in the customer survey. This is mainly attributed to the complicated and abstruse questionnaire, which is based on pairwise comparison with a nine-point scale, unlike the design of traditional questionnaires. Second, this study is not applicable to assessing individual impacts of product-related, marketing-related and customer-related influencing factors. This research focuses on establishing the iDSS to maximize NPD success, rather than investigating the individual impacts of various influencing factors. Sensitivity analysis is thus omitted in this research to examine such matter. Besides, in this research the proposed iDSS has been developed and validated with the support of information from a single company in the power tool industry. This may perhaps make the iDSS applicable to the power tool industry, or even only to the case company. Finally, companies may find difficulties implementing the iDSS. The proposed iDSS is comprehensive, requiring massive amount of information from different departments, such as marketing data, financial data, product specifications, and so forth. The data warehouse is a prerequisite to implement and operate the iDSS. To facilitate the decision-making process in NPD through iDSS, companies should ensure a high level of information accessibility and data transfer, authorizing the NPD team and managers to retrieve required information. Companies that lack a well-structured and systematic database may find difficulty implementing the iDSS. Besides, top management support and commitment are important in introducing and implementing the new iDSS in a company. The implementation of the iDSS may involve risks and uncertainties which may hinder the normal operation of the NPD process. The NPD team may also be reluctant to adopt new systems as training in documentation, information sharing, and knowledge integration is needed. The top management may be unsure about the iDSS and hence hesitate to replace the current NPD decision-making practice with the novel iDSS.

6.4 Suggestions for Future Research

With the above discussion, this research could be further improved while further research direction ascertained. Future research is suggested to emphasize the following:

- Better understanding how the various influencing factors impact each other would be helpful for managers to formulate NPD and marketing strategies. This research could hence be extended in the future by performing sensitivity analysis, and investigating the inter-relationships of these factors. For example, in order to test which factor exerts the greatest influence on the results of

Module III, all key parameters in sub-model 1, such as the attractiveness of product design, performance, quality, packaging, competitiveness, and overall customer satisfaction, could be systematically changed by a specific amount, for example increased and decreased by 5% of their original value. The impacts of such changes in each parameter on the results of Module III could then be analyzed. If the change of a parameter results in relatively large changes in the results of Module III, it could be interpreted that the results of Module III are sensitive to that parameter while its respective factor is more important in the module.

- The iDSS consists of three modules that are developed using different computer applications. To better connect these modules, it would be valuable if these modules could be merged together into a particular platform with respective interfaces using just a single application. This could highly expedite the data being processed and streamline the operation of the iDSS, thus reducing human errors and time in handling data, and making the decision-making process in NPD more efficient.
- The iDSS has only been applied in a single company in the power tool industry in this research to test its applicability. The iDSS can be implemented in other industries if any parties deem it appealing. Case studies could be conducted in a range of different industries to test the capability of the iDSS, and customizations could be made if necessary. Comparative research could then be carried out to examine their differences.
- The iDSS mainly focuses on the decision making for NPD with a consideration of customer satisfaction and needs. The voice of customers could help in product design and manufacturing, which also play an important role in the

NPD process. In this research, the voice of customers on product attributes listed in the evaluation scorecard was heard, and it could be translated into engineering parameters by using the method of quality function deployment. Future research thus could be done by creating and integrating such an additional module for product design and production.

APPENDICES

Appendix A: Schedule of This Research

Description	Duration
Phase 1: Background study - Review literature to study the background of NPD - Study the background of the case company - Identify the problem statements, research aim and objectives, as well as the research methodology	8 months (August 2007 – April 2008)
Phase 2: Development of the iDSS - Study various tools and techniques to help develop the iDSS - Examine the current practice of NPD of the case company - Conduct interviews to better understand the needs of the case company - Propose theory and develop a framework of the iDSS - Write research papers	20 months (February 2008 – September 2009)
Phase 3: Application and validation of the iDSS - Collect data from the case company as well as conduct interviews and a customer survey for case studies - Use obtained data to illustrate and validate the iDSS through case studies - Improve and re-validate the iDSS - Write research papers	18 months (June 2009 – November 2010)
Phase 4: Thesis writing/preparation - Draft and revise outline of thesis chapters and the table of contents - Draft and revise different chapters of the thesis, abstract, and acknowledgments - Check references and appendices - Format and proofread the thesis - Arrange temporary binding	8 months (August 2010 – March 2011)

Appendix B: Questionnaire Used in Customer Survey

A Survey of Consumer Buying Decision and Preferences

The purpose of this survey is to investigate the consumer buying decision in terms of their preferences for the product attributes, as well as their general perceptions of the existing products, particularly in the power tool industry. (The "products" mentioned in this questionnaire refers to power tools.)

Please contribute your valuable time to complete the following questionnaire. Your opinions collected can help improve the effectiveness and innovativeness of the new product development (NPD) in the related industry. All information in this survey will be used for research purpose and kept strictly confidential.

Rating Explanation:

Rating	Definition
1	Equally important
3	Moderately important
5	Strongly important
7	Very Strongly important
9	Extremely important
2,4,6,8	Intermediate values between the two adjacent judgments

Remark: If you experience any difficulties giving a rate to the question, please refer to the attached guideline (i.e., **SUPPLEMENTARY – A Guideline of Filling in the Form**).

PART 1: CONSUMER BUYING DECISION

Please indicate the relative importance of the following product characteristics when you "decide to buy or not buy" a product.

		Extremely important <---- Equally ----> Extremely important																	
Reliability:	Lower risk to user (e.g. bits do not fail out, and chucks do not require frequent retightening due to bit slippage)	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Long-lasting battery
Weight and size:	Light weight	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Compact size
Ergonomics:	Comfortable handle	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Well-balanced
Versatility:	Variable speed settings	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Multiple chuck and bit fittings
Convenience:	Built-in LED lights	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	One handed bit insertion
Carrying case:	To provide protection	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	To provide storage of tool and bits

Please indicate the relative importance of the following product characteristics when you "decide to buy or not buy" a product.

		Extremely important <---- Equally ----> Extremely important																
Quality:	Reliability	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Durability: the durability of surviving from drops
Design:	Weight and size	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Ergonomics: comfortable handle and well-balanced
	Weight and size	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Versatility: variable speed settings and multiple chuck and bit fittings
	Convenience	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Versatility
	Convenience	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Weight and size
	Versatility	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Ergonomics
	Ergonomics	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Convenience
Packaging:	Carrying case	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Warranty: longer warranty period

Please indicate the relative importance of the following product characteristics when you “decide to buy or not buy” a product.

		Extremely important <---- Equally ----> Extremely important	
Performance:	Robustness: the ability to endure tough applications	⑨ ⑧ ⑦ ⑥ ⑤ ④ ③ ② ① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨	Efficiency: to complete applications (e.g. drilling and fastening) quickly and easily
Competitiveness:	Price: reasonable price	⑨ ⑧ ⑦ ⑥ ⑤ ④ ③ ② ① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨	Time: quick response to market in launching new products
	Price: reasonable price	⑨ ⑧ ⑦ ⑥ ⑤ ④ ③ ② ① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨	Brand: well-known brand
	Brand: well-known brand	⑨ ⑧ ⑦ ⑥ ⑤ ④ ③ ② ① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨	Time: quick response to market in launching new products

Please indicate the relative importance of the following product characteristics when you “decide to buy or not buy” a product.

		Extremely important <---- Equally ----> Extremely important																	
Overall:	Quality	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Design
	Quality	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Packaging
	Design	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Competitiveness
	Design	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Packaging
	Packaging	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Competitiveness
	Packaging	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Performance
	Performance	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Quality
	Performance	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Design
	Competitiveness	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Quality
	Competitiveness	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Performance

PART 2: CUSTOMER PERCEPTIONS

The current product can satisfy your actual needs. ☐ Definitely ☐ Probably ☐ Maybe ☐ Probably not ☐ Definitely not

Please suggest if there are any other determining factors/criteria influencing your buying decision on power tools.

____

Please state if there are any product features that you desire or suggest to improve.

____

PERSONAL INFORMATION

Name:	______________________			Gender:	☐ M	☐ F
Age:	☐ <20	☐ 20-29	☐ 30-39	☐ 40-49	☐ 50-59	☐ ≥60
Education level:	☐ Primary or below		☐ Secondary		☐ Tertiary or above	
Employment status:	☐ Employed	Self-employed	☐ Unemployed	☐ Retired	☐ Homemaker	☐ Others:________
Avg. household income/month:	☐ ≤$10K	☐$10001-$30K	☐ $30001-$50K	☐ $50001-$70K	☐ $70001-$90K	☐ ≥$90001
Contact:	______________________					

Thank you for your contribution.

SUPPLEMENTARY: A GUIDELINE OF FILLING IN THE FORM

Question: Please indicate the relative importance of the following factors when you “decide to buy” a product.

Response 1: If you think “the Price is *Very Strongly* more important than Quality,” you can rate as follows:

	Extremely important <---------------------- Equally ----------------------> Extremely important																	
	9	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	
Quality	○	○	○	○	○	○	○	○	○	○	○	○	○	○	●	○	○	Price

Response 2: If you think “Quality is *Moderately* more important than Price,” you can rate as follows:

	Extremely important <---------------------- Equally ----------------------> Extremely important																	
	9	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	
Quality	○	○	○	○	○	○	●	○	○	○	○	○	○	○	○	○	○	Price

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