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INFUSION EFFECTS OF INNOVATIONS ON THE TECHNOLOGICALLY ORIENTED NEW PRODUCT DEVELOPMENT PROCESS

By

Rosanna Garcia

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ABSTRACT

INFUSION EFFECTS OF INNOVATIONS ON THE TECHNOLOGICALLY ORIENTED NEW PRODUCT DEVELOPMENT PROCESS

By

Rosanna Garcia

The primary objectives of this dissertation were two-fold: (1) to advance the practitioner's understanding of how adopted innovations can assist new product (NP) managers in driving the success of inventions, and (2) to advance the methodological framework of how the NP development process of technological firms can be studied as a dynamical system. A secondary question was to determine if 'catalytic' innovations significantly increase the success of an NP program. Two methodological approaches were used to study these objectives; a system dynamics model and a longitudinal study. The system dynamics model was prefaced by intensive case studies of two technologically oriented firms. The data collected in the longitudinal study were evaluated using bivariate linear growth curves using structural equation modelling.

It was found in both studies that the successful adoption of innovations into the firm has an indirect effect on the success of a NP program. Innovations successfully adopted into an organization have the effect of increasing a firm's competences in technology knowledge utilization (exploitation) and R&D proficiencies. These studies also reveal a positive relationship between technology knowledge exploitation and R&D proficiencies as explanatory variables to NP program success. Thus, indirectly the

successful adoption of innovation can drive NP success by helping organizations to better utilize their technology knowledge competences.

Technologically oriented organizations that are interested in using the adoption of innovations as a strategy for driving greater success in their NP program should focus on making resources readily available to the NP process, encouraging failures in NP design, and actively involving marketing in the NP process. An important finding supported by both the system dynamics model and the linear growth curve model was that adopting innovations can increase technological knowledge competences. However, the quadratic trajectories observed in the longitudinal study suggest that peaks in performance are often reached. The continual renewal of knowledge is important in the NP development process. Firms that structure themselves to be open to new knowledge will benefit not only in their success of adopting innovations, but also in NP program performance.

'Catalytic' innovations were identified in this study as innovations adopted into the organization that act as a catalyst to develop new inventions not previously planned prior the adoption of the innovation. Marginal support was found for the existence of 'catalytic' innovations in the sample population studied. Although catalytic innovations are not an essential prerequisite to ensure new product program success, when adopted in moderation they may substantially increase the firm's knowledge base for building new products. This increased knowledge can lead to increased new product program success.

DEDICATION

This dissertation is dedicated to my parents, Alice Perez Garcia and Frank G. Garcia, and my grandparents, Rosalie Rangel Perez and Marciano Duran Perez with immeasurable thankfulness for life and its wonders. It is also dedicated to Paul W. Rummel for without his love and support this dissertation would not have been completed.

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CHAPTER 1

INTRODUCTION

1.1 Background

The adoption of technological innovations has traditionally been seen as a means of improving productivity, reducing costs, and building core competencies in the manufacturing, distribution, and/or marketing processes of an organization (Robertson & Gatignon, 1986). From an organizational behavioral perspective, this research has primarily taken two different theoretical approaches: (a) studies investigating what factors facilitate the adoption of innovations in order to speed its diffusion (Damanpour, 1991; Rogers, 1995; Zaltman, Duncan, & Holbek, 1973) and (b) studies focusing on the effects from adopting innovations on organizational structure (Blau & Schoenherr, 1971; Repenning, 2001). From a marketing perspective, the adoption of innovations has often been studied to generate models of diffusion to consumers (Bass, 1969; Sultan, Farley & Lehmann, 1990).

The innovations adopted by firms traditionally have not been viewed as a resource for subsequently generating new innovations[1]. Yet, firms regularly adopt technological innovations to build competitive advantages, not as a means of improving internal productivity, but as a competitive strategy to invent new products for the marketplace. Two examples will help to demonstrate this point.

The California State Automobile Association (CSAA) is one of the largest

[1] 'new' innovations are those that are new to the firm or adopting entity although the innovation may already have been introduced into the marketplace (Garcia & Calantone, 2001).

providers of automobile, home and life insurance in California. It is not a firm that one would associate with technological advancements. However, recently it invested over $10 million in computer and telephony technology in order to introduce new services to their customers as a pre-emptive competitive move. By adopting technological innovations new to an insurance company, they were able to introduce an automatic call center and web services for processing claims. This has allowed the firm to expand their service offerings and preempt the competition.

Similarly, Comdel, Inc., a small electronics supplier to the semiconductor industry headquartered in Massachusetts, adopted a programmable memory chip in their user interface. This will allow them to introduce $500,000 worth of new products to their customers this year with that revenue predicted to grow exponentially over the next five years. The president of Comdel, Ted Johnson, admits to continually exposing the organization to innovations of all types: administrative, technological, and process. Exposure serves as a catalyst for introducing uncertainty into the R&D process with the hope of developing significantly more innovative products than the last generation.

These two examples show the adoption of innovations as a competitive strategy undertaken by firms for building their product portfolios, and not as a means for improving internal distribution or manufacturing efficiencies. The dissertation was motivated by this under-researched phenomenon where technological innovations are adopted by firms for the sole purpose of facilitating the invention of new products for marketplace distribution. Questions that arise when investigating this innovation strategy are: What is the effect of the adoption of technological innovations on new product success? What characterizes and differentiates the types of firms that use this new product development strategy? How should the new product development process adapt to accommodate the continual adoption of innovations new to the firm?

This dissertation looked at the influences of the adoption of innovations by a technological firm on innovations invented by the firm. The primary research question it addresses is "over time, how does the adoption of new innovations affect the new product development process, if at all?"

A secondary issue that was addressed is how does the firm evolve and adapt its organizational structure over time in order to effectively adopt innovations and subsequently produce inventions. The evolutionary theory of the firm is not new to organizational behavior researchers (cf. Nelson & Winter, 1974; Tushman & Romanelli, 1986, Miller, 1990; Aldrich, 1979) or to economic theorists (cf. Schumpeter, 1934; Perez 1983). As well, the evolutionary theory of technologies has been extensively explored (cf. Utterback, 1996; Christensen, 1997; Ziman and colleagues, 2000). The adoption of innovations into the firm itself has been modeled as an evolutionary process whereby innovations are invented, and out-dated inventions undergo exnovation[2] in order to free resources for future adoption of new innovations (Kimberly, 1981). The interaction between adopted innovations and the new product development process also can be viewed as an evolutionary system. This dissertation looked at the evolving new product development process as effected by the adoption of new innovations.

The remainder of this introduction is organized as follows: section 2 addresses the new product development as an evolving process. Section 3 introduces the model that was tested in this dissertation. Section 4 summarizes the methodology to be utilized to

[2] 'exnovation' is the removal of an innovation from an organization, a term coined by Kimberly (1981).

test the hypotheses, and section 5 provides research questions that intend to be answered from this study. Section 6 concludes this chapter with a summary.

1.2. The Evolving New Product Development Process

The new product development program process is characterized by nonlinear relationships and complex interactions that evolve dynamically over time. Field research supports this perception of a dynamic nonlinear evolving NPD program process. Van de Ven, et al (1999) conducted a seventeen-year long longitudinal study on the 'innovation journey' undertaken by organizations in their development of new products. They concluded, "our research of a wide variety of innovations has found no support for a stage-wise model of innovation development and no support for a linear (cyclical) model of adaptive trial-and-error [random] learning, particularly during highly ambiguous and uncertain periods of the innovation journey" (pg. 4). Thus, despite common practice by NPD researchers, the innovation program process should not be considered as following a static linear stage-gate process popular in many studies (cf. Cooper 1993).

Environmental conditions in new product development continuously change over time. The inventing organization must continually adapt to dynamic exogenous and endogenous influences in the marketplace. Competitive threats surface, customers alter product requirements, and technology advances exponentially to create instabilities in the new product development process. NPD team movement, mergers and acquisitions, management turnover, and funding constraints (advancements) add to the dynamic internal environment faced by NP managers. These 'agents' interact during the NPD process, causing evolutionary dynamic and path dependent relationships.

Figure 1.1 presents this model of the evolutionary NPD process as influenced by the adoption of innovations. The relationships between constructs will be further detailed in the following section.

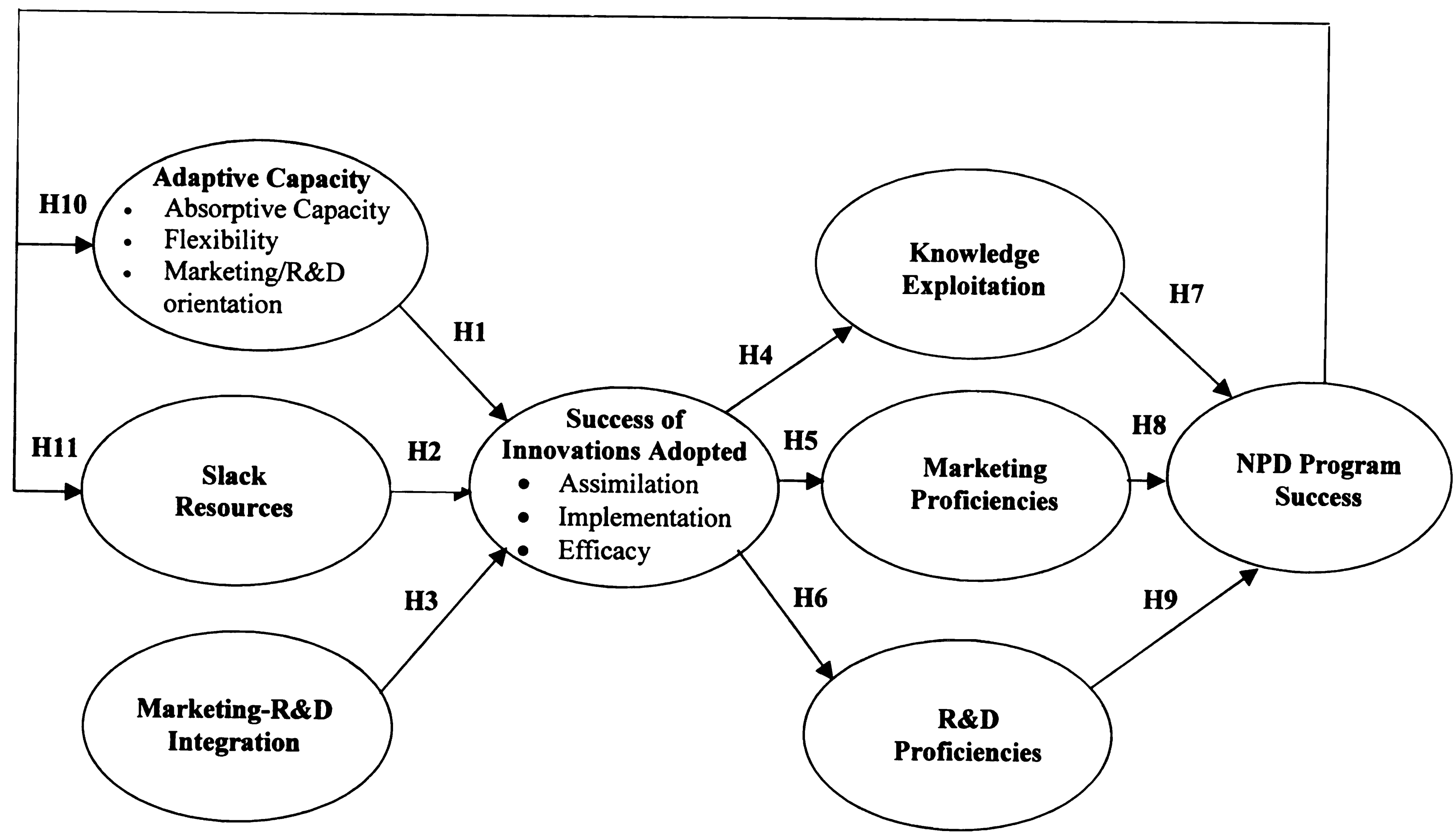
1.3 Model Introduction

In the model introduced in Figure 1.1, the antecedents to the adoption of innovations are a firm's adaptive capacity, its slack resources, and the integration between the marketing and R&D departments. Successfully adopted innovations are those that have been assimilated, implemented, and used effectively in the organization. The unsuccessful adoption of innovations is characterized by a failure to implement an innovation into the organization despite an expenditure of resources. It is proposed that the effects of successful adoption of innovations are to increase the firm's ability to exploit knowledge acquired through the adoption of the innovations and to improve the firm's marketing and R&D proficiencies. These gains in knowledge and proficiencies lead to greater new product program success. This new product program success ultimately affects the firm's slack resources and its adaptive capacity.

1.3.1 Adaptive Capacity

Evolutionary theory is concerned with how firms adapt to endogenous and exogenous environmental factors. The adaptation process has been described as following either 'punctuated equilibrium' or 'time-paced evolution'. The punctuated

Figure 1.1 Overall Model of Infusion Effects of Technological Innovations on the NPD Process



equilibrium model assumes that long periods of small incremental organizational evolution are interrupted by infrequent periods of discontinuous, radical change (Romanelli & Tushman, 1994; Abernathy & Utterback, 1978). The alternative explanation of the adapting organization embraces a more gradual evolution earmarked by continuous, although fast-paced, change over time (Eisenhardt & Tabrizzi, 1995). Eisenhardt and Tabrizzi claim that the ability to change continuously is a critical factor in the success of firms and that "product innovation is a primary way in which this alternative form of adaptation can happen" (pg. 84). This dissertation takes the perspective of time-paced evolution where firms are continually adapting to their endogenous environments.

Many studies have been conducted on the types of organizational structures that allow firms to quickly adapt to the environment and that facilitate the NPD process (Burns & Stalker, 1961; Miles & Snow, 1978). Burns & Stalker emphasized that an 'organic structure' appears to be required for conditions of change. Organic structures are characterized by a lack of rigid structure and definition, but with the ability to quickly respond to unstable conditions.

For adopted innovations to act as catalysts for inventions, they first must have successfully been assimilated into the firm. This requires the firm to be flexible and willing to adapt to the new ideas and new knowledge disseminated with the new innovation. Flexibility to learn quickly and to adapt to new information is essential for technological firms that must operate in turbulent market and technological environments typical of today's marketplace.

To remain flexible and adaptive the firm should monitor its external environment.

Adaptive organizations demonstrate this capability through a combination of their market and R&D orientation (Jaworski & Kohli, 1993; Slater & Narver, 1995; Hurley & Hult, 1998) and through their absorptive capacity (Cohen & Levinthal, 1990). Market orientation pertains to identifying customers' needs and wants, sometimes pre-anticipating the consumer's wants, and using this information in new product planning. The technology counterpart to market orientation, R&D orientation, is equally important as firms need to effectively respond to the ever-changing technological landscape in today's marketplace.

Fundamental to market orientation is organizational learning, which is the assimilation of information into the firm to increase knowledge. What the firm does with the information gained from monitoring the environment is as important as gathering the information itself. Cohen & Levinthal address this issue by coining the phrase 'absorptive capacity'. A firm's absorptive capacity is its ability to recognize the value of new information, assimilate it, and apply it to the development of new products. Thus, the construct, 'adaptive capacity' constitutes a firm's ability to gather and assimilate new knowledge, and subsequently adapt its new product strategy based on this knowledge accumulation. A firm's adaptive capacity is precursor to its ability to successfully adopt and implement new ideas, processes, or products.

1.3.2 Slack Resources

Slack resources are necessary for the development of inventions (Kamien & Schwartz, 1982); likewise, the availability of resources is required for the successful adoption of innovations by a firm. Availability of slack resources is determined by the successful market introduction of new products to the firm's customers. The greater the profits from new product introductions, the more resources become available to commit to new programs or technologies. Competition for resources can ensue as more technologies are invested in the firm. It was expected that the more slack resources available, the greater the likelihood that new technologies adopted by the firm are effectively assimilated into the firm.

1.3.3 Marketing and R&D Integration

Griffin & Hauser (1996) postulate that developing informal cross-functional networks between marketing and research departments enables more information to be communicated, increases coordination between the departments in decision making, and decreases new product uncertainty. This integration contributes to the successful invention of new products. Using the same reasoning, it is expected that informally integrated marketing and R&D departments should lead to an increase in the internal communication between the two groups and increase the successful assimilation and implementation of innovations adopted by the technological firm.

1.3.4 Successful Adoption of Innovations

"The adoption of innovation is generally intended to contribute to the performance or effectiveness of the adopting organization" (Damanpour, 1991, pg. 556). This dissertation was interested in the effects on the new product development process of the infusion of innovations. An innovation has been defined as "an internally generated or purchased device, system, policy, program, process, product or service that is new to the adopting organization" (Damanpour, 1991, pg.556). Some innovations adopted by organizations have the potential to significantly impact the NP process. March (1991) has suggested that "some new technology is so clearly superior to overcome the disadvantages of unfamiliarity with it, it will offer a higher expected value than the old technology"(pg. 83). This dissertation terms these types of innovations as 'catalytic'. Catalytic innovations are adopted into the organization and act as a catalyst to develop new inventions not previously planned prior to the adoption of the innovation.

1.3.5 Knowledge Exploitation

Moving away from a resourced-based view, which considers knowledge as a company asset, knowledge-based theory argues that knowledge is a process by which organizations evolve by adapting the body of knowledge shared by its members and that much of this process occurs at the tacit level (Nelson & Winter, 1974; Plotkin, 1994). This viewpoint challenges the idea of knowledge as an economic asset or commodity, and instead argues for 'knowledge as the skilled process of leveraging resources, where the knowledge is embedded in the organization' (Spender, 1996, pg. 54). Knowledge accumulation occurs at a systems level where individuals are agents for the organization's continually evolving knowledge base.

Extant literature suggests that a fundamental agent contributing to the evolutionary process is the learning experiences of the firm during new product development. During the innovation process, knowledge (both market and technological) is accumulated and assimilated in order to facilitate the successful marketplace introduction of new products. Exploiting the knowledge gained from the new technologies embedded within new products increases the potential for the firm to achieve higher levels of performance.

1.3.6 Marketing and R&D Proficiencies

A firm's proficiency at technical activities and its proficiency at marketing activities have been noted in numerous studies to be development process factors that drive new product success (Cooper & Kleinschmidt 1995; Montoya-Weiss & Calantone, 1994). Technical activities include the R&D process, testing of the product, trial production, and production startup. The marketing activities include customer orientation, competitive monitoring, program development, as well as launch activities.

1.3.7 The Feedback Loop

'Innovation' as a process implies a temporal perspective. In order to study new product development as a process, this dissertation utilizes feedback loops to model the effects of evolution. A cyclical causal relationship exists in which the agents involved in the NPD process influence one another and in turn, are influenced by the very agents they have interacted with during innovation. The success or failure of new products in the marketplace will have direct, although nonlinear, path dependent effects on the firm's slack resources and its adaptive capacity. Failures in the marketplace can mean either more or less resources committed to the adoption of innovations, depending upon the firm's new product strategy. Successes most frequently will result in an increase in slack resources, but with allotment constraints most likely imposed.

Likewise, the more successful a NPD project, the greater the commitment made to that new product development program, which frequently results in decreasing the adaptive capacity of the organization. It has been shown that firms that did not continually renew their knowledge stock lock themselves into old technological knowledge and lock themselves out of the ability to acquire new knowledge. This phenomenon is referred to as lock-in by Cohen & Levinthal, (1990), core rigidities by Leonard-Barton, (1995), or the Icarus Paradox by Miller, (1990). Lock-in to outdated knowledge and lock-out of new knowledge causes the firm to lose its flexibility and openness to new ideas. A firm must have a knowledge foundation that is continually updated in order to be able to assimilate the latest technological knowledge.

The feedback loop was evaluated using system dynamics modeling, which allows the evaluation of the nonlinear relationships between constructs over time. This methodology will be further discussed in Chapter 3.

1.4 Methodology

The systems model in Figure 1.1 was tested in two studies. System dynamics computer simulations were used in study 1 to test the model. Study 2 utilized a doubly multivariate longitudinal study[3] (Bijleveld, et. al, 1998) to further provide support for the model introduced here. Utilizing these two methods for studying the model not only allowed testing the external validity of the simulation model, but also provided an opportunity for reconciling actual new product practices with the theory developed here.

System dynamics modeling has long been utilized in operations and strategic management research (Forrester, 1987; Morecroft and Sterman, 1994; Nelson and Winter, 1974; Repenning, 2001; Sastry, 1997). Nelson and Winter's (1974) seminal work proposed an evolutionary theory of economic change based on the continual development of innovations. They used computer simulations to model this dynamic system in order to study the interactions among market structures, R & D spending, technical change, and

[3] doubly multivariate designs survey multiple respondents in multiple groups on multiple variables over multiple waves (Bijleveld, et al 1998).

other aspects of industry performance.

Janszen (2000) recently used system dynamics modeling to study the peculiarities of the new product process. He argues that non-linear mechanisms resulting from the interaction of the different factors involved in NPD are responsible for the unpredictable dynamics of the process. The new product development process can be best described as an evolving dynamic complex system, and thus, was studied from this perspective in this dissertation.

A system dynamics modeling software was utilized to evaluate the continuous process as the firm adapts itself to the innovations it adopts, and subsequently, invents new products. Ventana Systems' Vensim (2001) was used for the model test. The internal and external validity of the model was validated using the methods suggested by Levine, Van Sell and Rubin (1992). This involves conducting structural tests, behavioral tests and policy tests, all of which will be elaborated upon in Chapter 3. A sensitivity analysis was performed to learn more about the importance of the various parameters in relation to certain structural characteristics of the model. The objective of the sensitivity analysis was to learn more about the effects of changes in the parameters of the system. It is the equivalent of running 'what if' scenarios (Janszen 2000).

Computer simulations allow numerous factors to be modeled into the system, and thus, the problem becomes one of determining: what are the important exogenous factors not explicitly defined in the model under study to be set as ceteris paribus, what are the appropriate mathematical models that explain the relationships between variables, and what are appropriate initial values for modeling the dynamic system? In the first study, an in depth case study of an electronics firm involved in the semiconductor industry was undertaken to answer these questions. The results of the computer simulation provided the insights necessary to compile a relevant and concise survey for distribution to a large sampling frame.

The second study utilized a longitudinal survey methodology on 40+ technology firms with 2-3 respondents per company. Data was collected at three points in time five months apart. This time lag was partially selected for convenience[4] (Jap 1999) and partially because new product development projects typically take 9-36 months from original concept to launch (Griffin, 1997). Since the unit of analysis was the NP development program of the firm or division, this ten-month period reflects the changes within a new product development program from the infusion of technological innovations at different stages of the adoption process.

To maximize the sample size and reduce attrition over time, a minimum of two respondents from each company were asked to complete the survey. A modified Dillman (1978) approach was utilized in soliciting survey response. This consisted of three waves of mailings where the first and third waves are the survey instruments and the second mailing is a postcard reminder.

Six of the eight constructs in the model have been used in numerous studies, thus, the scales were borrowed or adapted from previous empirical research. Measures for 'adaptive capacity' and 'knowledge exploitation' have not been previously reported. 'Adaptive capacity', was based on the well-documented concepts of absorptive capacity, flexibility, and marketing/R&D orientation originating in the management and marketing

[4] six months or less between sampling was suggested by Sandy Jap in personal correspondence.

literature. Measures for these concepts have been reported in the literature, and form the measures for the new construct, 'adaptive capacity'. Likewise 'knowledge exploitation' was based on the well-cited works of Cohen and Levinthal (1990) and March (1991). Measures for this construct have not been reported in the extant literature. The measures, thus, were based on the theoretical models suggested by these researchers.

Convergent validity and discriminant validity were tested using confirmatory factor analysis (Fornell & Larker 1981; Anderson & Gerbing 1988). Measurement reliabilities evaluated using Cronbach's alpha coefficient (Nunnally 1978). Content validity was ensured in the development of the survey by pretesting the instrument with managers and other researchers knowledgeable about the new product development process.

Three data collection points allow the full structural model to be tested using growth curve modeling techniques in EQS (Bijleveld, 1998). Structural equation modeling (SEM) tests interdependencies and interrelationships among the constructs, as well as evaluates the total effect of the antecedents on the dependent variables. All methodology is further developed in Chapter 3.

1.5 Research Questions to be Answered

The primary research motivations of this study are to fully develop and test the proposed model of the adoption of innovations as well as to explore the evolutionary nature of the firm as it adapts to the changing internal environment instigated by the adoption of new innovations.

The objectives of this dissertation are two-fold: (1) to advance the practitioner's understanding of how adopted innovations can assist new product managers in ensuring the success of invented innovations, and (2) to advance the methodological framework of how to study the NP process of technological firms as a dynamical system. Thus, two sets of research questions ensue:

1.5.1 Practitioner Oriented Questions

PQ1 Can the adoption of innovations into the firm contribute to the success of new products?

(i) Can the adoption of innovations act as a catalyst to the successful invention of new products?

(ii) Does the successful adoption of technological innovations lead to an increase in the number of new product development projects undertaken by the firm?

(iii) What resources and types of organizational cultures (adaptive/rigid, integrated/decentralized marketing-R&D, limited/moderation/excess resources) promote the successful adoption of innovations into the firm?

PQ2 How should firms structure themselves to increase the successful adoption of new innovations?

PQ3 What effects do the successful adoption of innovations have on lock-in (core rigidities) and lock-out of knowledge?

1.5.2 Theoretical/Methodological Research Questions

TQ1 Does a relationship exist between the adoption of innovations and the successful invention of new products in the technological firm? Is this relationship nonlinear?

TQ2 Is adaptive capacity an antecedent to the successful adoption of innovations? How should it be operationalized?

TQ4 From a methodological perspective, does system dynamics modeling better represent the evolving new product development process compared to more traditional linear representations?

By undertaking both sets of questions the intent of this dissertation was to advance academic and practitioner knowledge about the innovation process. The results should be interesting to new product managers who must understand the factors that lead to success in the marketplace through the continual development and introduction of new products. Academics should benefit from the advancement in theory about the evolving innovation process and the role of adopted innovations in the NPD process.

1.6 Summary and Overview of the Remaining Chapters

Chapter 1 provided an overview of the focus of this dissertation. A conceptual model was presented which proposes relationships among the construct 'success of innovations adopted', its antecedents, and its resulting outcomes. The research objectives and questions addressed in studying this model were also introduced. Chapter 2 will further develop the theoretical foundation of this model by presenting a literature review on the adoption of innovations and building the hypotheses, which were tested in this dissertation.

Chapter 3 will provide an overview of the methodology, which were used to test the hypotheses detailed in Chapter 2. Chapter 4 details the results of the system dynamics model, and Chapter 5 presents the results of the longitudinal survey. Chapter 6 summarizes the dissertation with conclusions and contributions.

CHAPTER 2

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1 Domain Delineated

The adoption of innovations has been studied from numerous perspectives: economics (Dosi, 1990; Freeman, 1988; Perez, 1983), management science (Dewar & Dutton, 1986; Damanpour, 1991), organizational behavior (Baldridge & Burnham, 1975; Kimberly, 1981), and sociologically (Rogers, 1995). Because of these diverse approaches to studying the adoption of innovations, it is important to set the domain of this dissertation.

2.1.1 Unit of Analysis and 'Innovation' Domain

The unit of analysis for this study was the NPD program at the division level. For firms without multiple divisions, 'firm' is used interchangeably with 'division'. Reference to a 'division' also pertains to the strategic business unit (SBU). In this study, 'organization' is used interchangeable with 'firm', with both terms referring to profit-seeking corporations.

This dissertation studied only *technological* innovations as opposed to the managerial or administrative innovations commonly studied from an organizational perspective. 'Innovation' has been defined as an iterative process initiated by the perception of a new market and/or new service opportunity for a technology-based invention, which in turn leads to development, production, and marketing tasks striving for the commercial success of the invention (Freeman, 1994). Technology-based innovations are those innovations that embody inventions from the industrial arts, engineering, applied sciences and/or pure sciences. Examples include innovations from the electronics, aerospace, pharmaceuticals, and information systems industries.

Additionally, although this theory applies to product and process innovations, the focus of this dissertation was on technological *product* innovations. Product innovations are new products or services introduced to meet an external user or market need (Knight, 1967; Utterback & Abernathy, 1975). Damanpour and Evan (1984) even distinguish between a technical innovation and a technological innovation. "Technical innovations…are not merely innovations resulting from the use of technology. They are defined as innovations that occur in the technical system of an organization and are directly related to the primary work activity of an organization. A technical innovation can be the implementation of an idea for a new product or new service or the introduction of new elements in an organization's product process or service operation" (pg. 394). Technological innovations are broader and encompass technical innovations as well as any innovation embodying a technology.

It is important to elucidate that an invention does not become a product innovation until it has processed through production and marketing tasks and is diffused into the marketplace (Freeman, 1994; Layton, 1977; Smith & Barsfield, 1996). This dissertation looks at the influences of *innovations* adopted by the firm on the *inventions or new products* created by the firm for future marketplace distribution. Innovations will most likely originate from outside the company whereas inventions must be invented within the firm for the focus of this dissertation. In order to distinguish between the innovations adopted by the firm and the innovations created by the firm, the terminology, 'innovation' refers to adopted innovations and 'invention' or 'new product' refers to created-in-house innovations, even those that the adopting firm has introduced to the market.

2.1.2 Adoption vs. Diffusion of Innovation

Another important distinction is the focus on the adoption of technological innovations and not on the diffusion of technological innovations into the organization. This is important because many researchers have emphasized that the process of innovation continues as the innovation diffuses into the marketplace. This implication is made in Freeman's definition whereby 'innovation' is not just an entity but instead a process. Innovations evolve due to end-user customization. These innovations are frequently referred to as 'incremental' innovations. This dissertation does not address the diffusion process or how innovations evolve during diffusion. It assumes that a firm has adopted a technological innovation and that the innovation may or may not be customized by the adopting firm. Kimberly (1981) distinguishes between diffusion and adoption. "Diffusion is the process whereby an innovation spreads in a population, adoption is a process which results in a decision by potential adopters to invest resources in an innovation" (pg. 86).

The next question to arise was: "when is an innovation considered adopted?" Answers to this question have varied in the literature. An innovation may be considered as having been adopted once the decision about adoption has been made (Walker, 1969; Daft and Becker, 1978), once the implementation process has been initiated (Evan & Black, 1967) or after it has been successfully implemented (Mohr, 1969; Rowe and Boise, 1974). For the purposes of this study, a technological innovation is considered once the implementation process has been initiated. The reason for this focus was to be able to model how the new innovation alters the new product development process over time from the first decision to adopt the innovation until its full assimilation into the firm.

It is also important to define what constitutes the successful adoption of an innovation and what comprises the unsuccessful adoption of an innovation. Most studies on the adoption of innovations have used a positive decision to adopt as a measure of the dependent variable, success. However, Tornatzky and Klein (1982) and Robertson and Gatignon (1986) both argue that a measure of success should be the adoption decision <u>and</u> implementation of the innovation. Robertson and Gatignon use measures of the 'depth of use' of the technology and the 'degree of use'. This dissertation considered the successful adoption of an innovation as one which has a high degree of assimilation (depth of use) and a high degree of implementation (degree of use) along with a high degree of efficacy (degree of usefulness). The unsuccessful adoption of an innovation is characterized by a low degree of assimilation, implementation and efficacy. An innovation should not be considered a failure if it falls low on just one of these scales. Often an innovation is pertinent only to a single department. For example, the Linux operating system is more useful to an engineering department and may not even be implemented in a firm's marketing department. This would not make it unsuccessful in its adoption by the firm. For this reason 'dissemination', which describes the percentage penetration through an industry or organization, was not considered in the measure of the success of innovation adoption in this dissertation. Dissemination does not consider assimilation or efficacy.

2.1.3 Domain Summary

In summary, the focus of this dissertation was on the effect of the adoption of a technological innovation on the success of new inventions created by the firm and the evolutionary changes a firm undergoes to continually invent and market new products. A case in point would be the CSAA example cited in the introduction. This insurance company adopted voice-processing equipment (technological innovation) in order to provide new services (invention) to their customers. The voice processing equipment was most certainly adapted to the unique requirements of the CSAA, but more importantly, for the focus of this dissertation, the firm used this technological innovation to develop new services for their customers thereby becoming more competitive. Even though voice processing can be considered a well-diffused technology (introduced into the market in the late 70s), it was a new innovation to CSAA that resulted in new inventions for their customers. It was a widely implemented innovation with high efficacy for the firm and a high degree of assimilation since all employees of the firms were ultimately affected by the new technology.

2.2 The Evolutionary Nonlinear Dynamic Complex System

The model presented in chapter one was described as an evolving nonlinear dynamic complex system. Complex systems take on many meanings in the organizational and management literature. Traditionally it has been used to describe an organization with many interconnected departments, strategic business units or a large number of employees (Blau & McKinley, 1979; Blau & Schoenherr, 1971; Mileti, Gillespie & Haas, 1977). The greater the number of interacting members in the organization, the greater is its complexity. It has been argued that complexly structured organizations are more likely to be innovative compared to less complex ones (Aiken & Hage, 1971; Baldridge & Burnham, 1975; Moch & Morse, 1977).

Complex systems are mainly characterized by the phenomenon that small disturbances in the system can multiply over time because of nonlinear relationships and the dynamic repetitive nature of the system. These small perturbations in the system can have large impacts, although the impact may not be observed until a later point in time. It is because of the feedback inherent in complex systems that these small seemingly irrelevant noises can be amplified and molded into larger more influential phenomena.

Complex systems exhibit self-reinforcing positive and negative feedbacks that invoke path dependencies. These path dependencies in turn create nonlinear relationships among the interacting parts (agents) of the system. Disruptions originating in one part of the system, in effect, propagate forward and backwards along the chain. For example, the success of an innovation can create a positive self-reinforcing phenomenon called increasing returns (Arthur, 1990). Exponentially positive returns are granted to the product with the highest market share (e.g., VHS). Likewise, failed products rarely can turn around their diminishing returns and face negative self-reinforcing nonlinear profit levels (e.g., Betamax).

2.2.1 The NPD Process as a Complex System

The new product development (NPD) program process can be described as an evolutionary nonlinear complex adaptive system. The NPD program includes the full portfolio of new product projects under development by the firm. The NPD process *rarely follows a linear path* of product invention as set forth in the stage-gate process popular in practitioner oriented reference books (Cooper, 1993). It is an evolving system as innovations are continually invented by the firm to address the dynamic marketplace. Complexity ensues as the agents continually interact with each other and the environment causing the NPD process to adapt to the changing environment. The strategic goals of the firm may not necessarily be changing, but the agents within the NPD process are dynamic. Exogenous factors such as competitors, customer demands, regulatory agencies, and/or technological developments may cause firms to alter their NPD process. Likewise endogenous factors such as resource availability, skills sets of the NPD team, managerial turnover, and/or organization-wide strategic changes can cause alterations in the NPD process. Nonlinear relationships results as feedbacks from both endogenous and exogenous factors result in further adaptations to the NPD process. The question is: how does a technological firm develop a new product development program strategy for this type of dynamic process? It is argued in this dissertation that one way for technological firms to remain adaptive in evolving environments is to maintain a steady supply of catalytic innovations in its knowledge arsenal that facilitate the invention of new products.

In complex systems it is difficult to plan how the agents in the system will interact with each other. Two ideas or innovations, which may appear to be completely unrelated, can join together to organize into a larger unexpected idea. The internet evolved in this fashion as an organization's need to keep informed on projects (CERN) melded with the US Defense systems need for wartime communication to form a very complex but highly integrated vehicle for the public to share information with each other. Many other examples of this type of organization of system agents exist in the historical archives of new products.

Based on this foundation of the NPD process as a complex adaptive system, the role of a 'catalytic innovation' should become more evident. A catalytic innovation is an innovation that when introduced into the complex system will react with the other agents[5] within the system. This reaction may result in a new product idea or a new process, and may evolve into a new invention for the firm. The resulting reaction may not be immediately evident in the system as complex systems are time and path dependent. It is also feasible that no reaction between agents will occur at all. It is the focus of this dissertation to look at catalytic innovations to determine if firms can increase the success rate of their new product development programs through the adoption of these types of innovations.

2.2.2 Modeling of Complex Systems

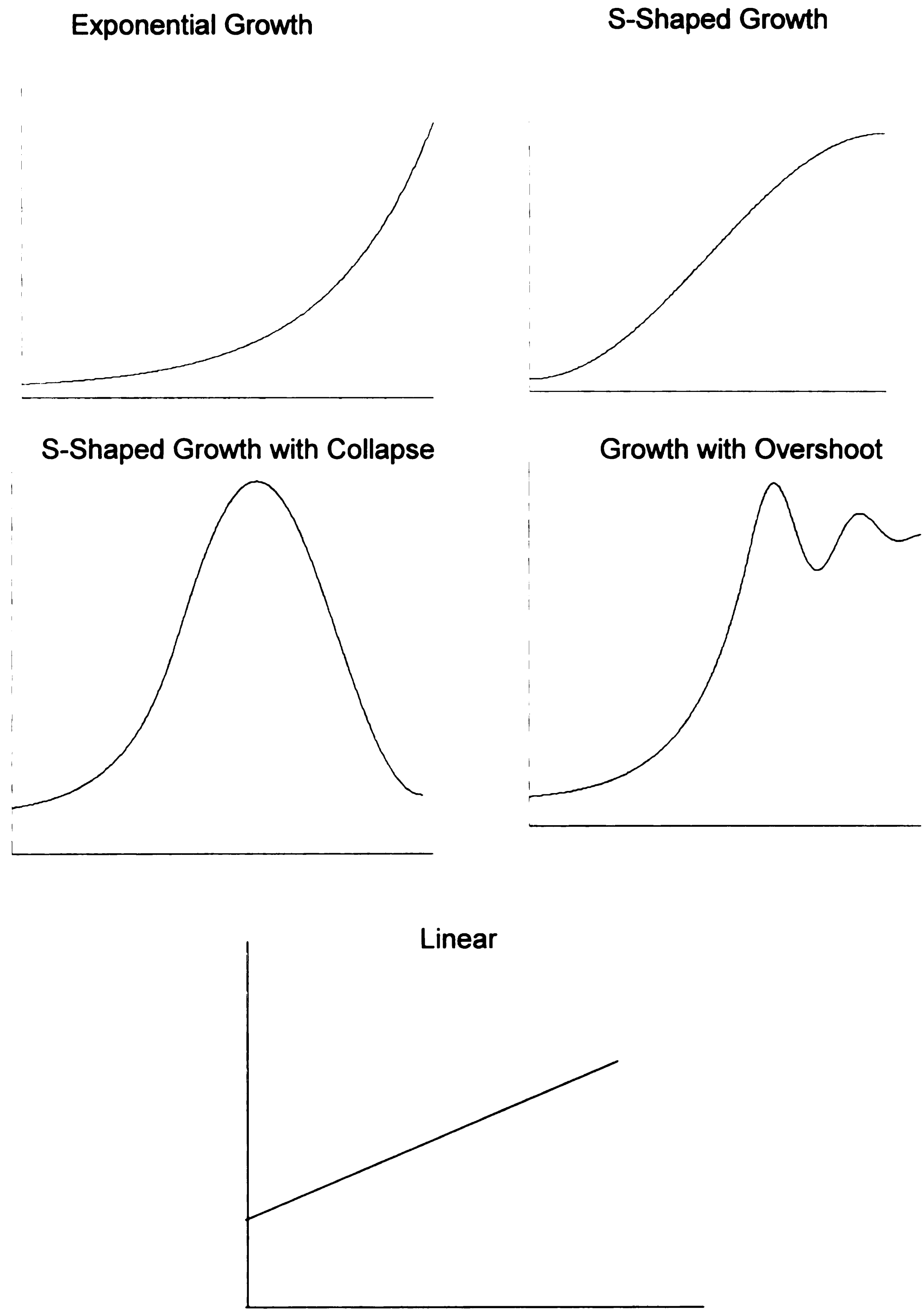
There are many methods of modeling complex systems (Daneke, 1999). This dissertation used a system dynamics model to evaluate the nonlinear relationships in the new product development process. A brief summary here will provide an explanation to the typical types of relationships that emerge in studies of system dynamics. Sterman (2000) identify four common modes of behavior in dynamic systems: 'exponential growth', 'S-shaped growth', 'growth with overshoot', and 'overshoot and collapse'. Exponential growth arises from positive (self-reinforcing) feedback. The advancements in semiconductor integrated circuits can be described as exponentially growing. Most systems cannot maintain such a rapid growth rate over an extended period of time. Limitations imposed on the system will impede growth. Sterman calls this constraint on

[5] In this dissertation, agents are the factors (constructs) that will be tested. Thus, 'knowledge exploitation' is an agent. From this point forward, factor will be used instead of 'agent'.

an otherwise positive linear or exponential relationship as the system's 'carrying capacity'. Exponential growth with a carrying capacity constraint describes the S-shaped growth curve, which has commonly been used to model the diffusion of innovations (Rogers, 1995) and product performance over time (Utterback, 1996). S-shaped growth models negative feedbacks that constrain growth. "Often however, there are significant time delays in these negative loops. Time delays in the negative loops lead to the possibilities that the state of the system will overshoot and oscillate around the carrying capacity" (Sterman, 2000, pg. 121). This results in S-shaped growth with overshoot. Carrying capacity however is not fixed. Erosion of carrying capacity creates a second negative feedback also limiting growth. If carrying capacity is itself dynamic, at the peak of the curve, carrying capacity is at its maximum. Collapse occurs in the system as the carrying capacity is eroded. This results in overshoot and collapse. This has been used to describe the rate of product or process innovation (Utterback, 1996). These are common relationships predicted to be observed in this dissertation. Figure 2.1 graphically demonstrates these fundamental modes in business dynamics.

With the domain of this dissertation addressed, the following sections will provide further elaboration on the model of infusion effects on the NPD process introduced in Chapter 1.

Figure 2.1 Fundamental Modes in Business Dynamics



2.3 Background Literature on the Adoption of Technological Innovation

Extant literature has attempted to understand the motivations for the adoption of innovations into organizations (Damanpour, 1991), the diffusion of innovations among organizations (Czepiel, 1974), or the rate of organizational innovativeness by adopting innovations (Daft & Becker, 1978; Zaltman, Duncan & Holbek, 1973). In nearly all studies of the adoption of innovations, there is an attempt to relate innovative behavior to organizational structure (e.g., centralization/formalization), departmental factors, or personal characteristics of the organizational personnel (e.g., risk averse/authoritative managers).

Empirical analyses have focused on the antecedents that facilitate the adoption of technological innovations. To account for the variations in patterns of organizational adoption of innovations, researchers have empirically tested four general categories: (a) attributes of organizational structure, (b) individual characteristics of organizational members, (c) environmental influences, and (d) the attributes of the innovation being adopted . Damanpour (1991) and Tornatzky and Klein (1982) conducted thorough meta-analyses on the adoption of innovations although from two different perspectives, which are now outdated. Damanpour focused on the organizational structure of the firm whereas Tornatzky and Klein focused on innovation attributes. Damanpour used organizational innovativeness or rate of adoption of innovation as the dependent variable (DV) whereas Tornatzky and Klein used adoption (yes/no) and, when available, implementation as the DV.

Damanpour found that specialization (diversity of specialist), functional differentiation (number of unique departments), and external communication had a positive influence on the adoption of technical innovations by firms while centralization had a negative effect. Formalization and vertical differentiation (degree of hierarchical levels) were found to have non-significant effects. Tornatzky and Klein found that compatibility and relative advantage of the innovation was positively related to its adoption. Complexity of the innovation was negatively related to adoption, whereas cost of an innovation and trialability were found to be insignificant. Although they did not test their propositions, Robertson & Gatignon (1986) suggested that competitiveness, technology standardization, industry heterogeneity, professionalism, and demand uncertainty positively relate to the diffusion and adoption of innovations. From an environmental perspective, Baldridge and Burnham (1975) reported that high environmental uncertainty and diversity encourages the adoption of innovations. In hospitals, Meyers and Goes (1988) determined that the environmental factor, community urbanization, was significantly correlated with innovation assimilation. The antecedents tested as predictors of innovation adoption have been numerous and the results varied.

Post-adoption outcomes are relatively less developed in the extant literature. A few empirical studies have reported the positive effects of the adoption of innovations on performance. Armour & Teece (1978) showed that the adoption of an administrative innovation increased the rate of return on owner's equity. Damanpour & Evan (1984) reported that a balanced implementation of administrative and technical innovations lead to higher performance in public libraries.

Most studies have ignored how the organization utilizes the innovation. Those studies that have addressed 'what happens after adoption' take an organizational behavior approach and focus on the resistance to implementation of new innovations (Repenning, 2001; Leonard-Barton, 1995; Klein & Sorra, 1996). It is interesting to note that in the organizational literature, a firm's innovativeness has been modeled as its willingness to adopt innovations (Damanpour, 1991; Han, et al., 1998) although how this innovativeness leads to new products is never expounded upon. The infusion effects of technical innovations on the new product process appear to be an under-researched area. This dissertation looks to address the infusion effects of the adoption of innovation on the dynamic new product process.

2.4 Hypotheses Developed

In this section, hypotheses, which were used to test the model as introduced in Figure 1.1, are formulated.

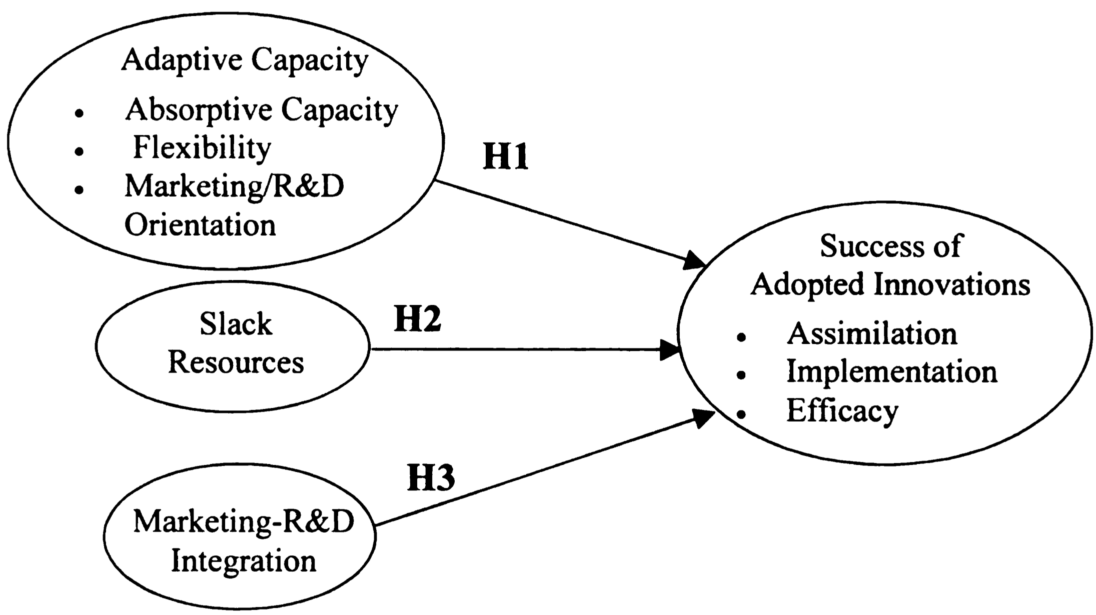
2.4.1 Antecedents to the Successful Adoption of Innovations

This section formulates the hypotheses of the model delineated in Figure 2.2. Adaptive capacity (H1), slack resources (H2), marketing-R&D integration (H3) are antecedents to the successful adoption of innovations into the organization. The successful adoption of innovations has previously been identified as those innovations that have a high degree of assimilation (depth of use), implementation (degree of use) and efficacy (degree of usefulness) within an organization.

2.4.1.1 Adaptive Capacity as a Construct

A firm's adaptive capacity describes how well a firm can adapt to dynamic environments. Weick (1998) found that firms with lower adaptive capabilities are more bureaucratic in structure and inflexible in strategy. Lewin, Long & Carroll (1999) found the more bureaucratic an organizational structure, the lower its absorptive capacity for new knowledge and the lower its abilities to recognize new opportunities, particularly in regards to the development of new products. New product development is viewed as one important way that organizations can adapt to changes in markets, technology, and competition. Adaptive capacity encompasses a firm's flexibility to adapt to changes, to absorb new knowledge, and to have a marketing and technology orientation. These measures are elaborated upon below.

Figure 2.2 Antecedents to the Successful Adoption of Technological Innovations



2.4.1.1.1 Flexibility

Flexible organizations quickly adapt to their environment and rapidly respond with strategies and inventions to address the dynamic marketplace. These types of organizations have been labeled as 'organic' (Burns & Stalker, 1961), or as 'prospectors'

(Miles & Snow, 1978). These firms are characterized as lacking in bureaucratic rigidities and high administrative intensity and rapidly build intuition and flexible options in order to learn quickly about and shift with uncertain environments (Tyre & Orlinkowski, 1994).

"In general, flexibility sustains any complex system. To respond to complex and changing markets, firms must maintain a variety of resources, routines, and robust intellectual processes. Monolithic responses are displaced by diverse strategies and activities. Organizational diversity, product diversity, life cycle diversity, customer diversity, and strategic business unit diversity help firms pursue business opportunities" (Phillips & Tuladhar, 2000, pg. 28). Flexible firms demonstrate high market and R&D orientations.

2.4.1.1.2 Market & R&D Orientation

Market orientation refers to the generation of market intelligence pertaining to current and future customer needs, dissemination of the intelligence across departments, and responsiveness to the intelligence collected (Kohli & Jaworski, 1990; Narver & Slater, 1990). The first step in building a market orientation is the generation of market information regarding competitors, technology evolution, and the current and future needs of customers, latent as well as expressed (Narver, et al., 2000). Information disseminated throughout the organization together with strategies developed and implemented in response to the information gathered constitute the full realm of market orientation.

Complementary to market orientation is a firm's R&D orientation. R&D orientation includes the generation and dissemination of technology intelligence as ways of monitoring technological advances that may be important to help identify catalytic innovations. It also refers to the firm's responsiveness to this technology intelligence. Berthon, et al (1999) introduced a similar concept called 'innovation orientation'. An innovation orientation however focuses on "openness to innovation" (Zaltman et al, 1973) and "a capacity to innovate" (Burns & Stalker, 1961). An innovation orientation is equivalent to the 'responsiveness' component of market orientation but does not include the generation of technology intelligence or dissemination of the information collected.

Market orientation has been closely linked with organizational learning (cf. Day 1994; Hurley & Hult, 1998; Kohli & Jaworski, 1990; Narver & Slater, 1990; Narver et al, 2000) as well as should R&D orientation. A firm may monitor the marketplace and utilize the information gained from the intelligence collection and still not learn from the data collection. Reasons for this lack of knowledge accumulation can be explained by a firm's absorptive capacity.

2.4.1.1.3 Absorptive Capacity

Absorptive capacity is defined as a firm's "*ability* to recognize the value of new information, assimilate it, and apply it to commercial ends" (Cohen & Levinthal, 1990, pg. 128, emphasis added). Whereas marketing and R&D orientations describe a cultural position regarding the collection of intelligence, absorptive capacity's focus is on the firm's *ability* to use the information to accumulate knowledge and apply that knowledge in the development of new inventions. Absorptive capacity focuses primarily on technological information but does not preclude market intelligence.

Absorptive capacity is path dependent. Cohen & Levinthal argue that the firm's ability to evaluate and utilize outside knowledge is highly dependent upon the level of prior related knowledge. They expound on this idea:

> "By having already developed some absorptive capacity in a particular area, a firm may more readily accumulate what additional knowledge it needs in the subsequent periods in order to exploit any critical external knowledge that may become available. Second the possession of related expertise will permit the firm to better understand and therefore evaluate the import of intermediate technological advances that provide signals as to the eventual merit of a new technological development. These revised expectations, in turn, condition the incentive to invest in absorptive capacity subsequently" (pg. 136).

A firm's absorptive capacity is highly dependent on the individuals within the firm who act as gatekeepers of information in boundary spanning roles. Knowledgeable gatekeepers monitor the environment and translate technical information into a form understandable to the internal staff. Thus, while R&D orientation is a cultural aspect of the firm, absorptive capacity addresses the structure of the firm to position capable personnel in positions that will allow the successful assimilation of market and technology intelligence.

To summarize, adaptive capacity explains a firm's propensity to be structured flexibly (organically), its readiness to build marketing and R&D orientations, and its ability to utilize the intelligence collected from monitoring the market and technology environments for developing new products. A firm's adaptive capacity was measured with these three different types of scales.

2.4.1.2 Adaptive Capacity as an Antecedent

As described above, a firm's adaptive capacity is defined by how well it can adapt to dynamic environments. Thus, firms with high adaptive capacities should have greater success at assimilating catalytic innovations into the organization. It has been shown that many innovations are either not adopted or not successfully implemented within the organization because of internal resistance (Klein & Sorra, 1996; Repenning, 2000) or because of the lack of flexibility within the organizational structure (Kimberly, 1981).

All firms have capacity constraints. When a capacity constraint is reached the firm becomes inefficient, or reaches a point of chaos. At this point, too many options are available for a firm to consider the appropriate action to take. If a firm has too much flexibility, it lacks the structure to set organization-wide strategic plans. If it collects too much intelligence, the knowledge base fails to expand because of 'information overload'. Similarly, firms must be concerned with 'lock-in' or what Leonard-Barton (1995) refers to as 'core rigidities.' This phenomenon occurs when a firm is so ingrained in a particular technology and knowledge base that it is unable to adapt to changing market conditions due to the rigidities in the firm. Too much knowledge is accumulated in one area, locking the organization from learning from new intelligence accumulated. March (1991) terms this as an imbalance in knowledge exploration compared to knowledge exploitation. An organization may focus too much on gathering information instead of utilizing the information to adopt innovations. Because of the imbalance in knowledge exploration, a nonlinear relationship exists between a firm's adaptive capacity and the successful adoption of innovations. Thus,

H1: The relationship between a firm's adaptive capacity and its successful adoption of innovations follows over time a nonlinear path of S-shaped growth.

2.4.1.3 Slack Resources

Organizational slack resources determine whether the organization can afford to adopt innovations. Slack resources have been defined as those resources that have not been committed to other organizational departments or programs. "The existence of slack means that the organization can afford (1) to purchase costly innovations, (2) to absorb failures, (3) to bear the costs of instituting the innovation, and (4) to explore new ideas in advance of actual need" (Rosner, 1968, pg. 615). Slack resources are not just monetary assets. They also include human, physical, and temporal resources. Is there knowledgeable staff with available time to make decisions about new innovations? Does the firm have the proper computer systems, equipment, and/or building sites necessary to ensure the successful implementation of a new innovation? Are slack manufacturing capacity, R&D capabilities, etc. available to assimilate the innovation?

In their study on the adoption of innovations, Dewar and Dutton (1986) found that the greater the number of specialists in an organization, the more easily new technical ideas can be understood and procedures developed for implementing them. Likewise, Robertson & Gatignon (1986) found that R&D allocation lead to enhanced technologies. Although Damanpour (1991) expected to find, in his meta-analysis on the adoption of innovations, a positive relationship between slack resources and the successful adoption of innovations, he found a non-significant relationship. He did however, find a significant positive relationship between technical knowledge resources and adoption success. Technical knowledge resources "reflect an organization's technical resources and technical potential" (pg. 589).

Fenell (1984) warns that researchers should consider whether parallel competing innovations factor into the adoption of innovations. "Parallel innovations may pose competing alternatives for the use of slack resources, either because two or more innovations may have developed simultaneously in the same substantive area or because different innovations may represent alternative ways of expending resources (Kimberly 1981)" (pg. 114). Organizations will not have unlimited funds available for adopting all the innovations they believe beneficial to the production of inventions. Even when slack resources are readily available, management will very likely impose a cap on the percentage available for new innovations. Additionally, by definition, slack resources allow the firm to absorb failures. With an increase in slack resources, managers will be comfortable making risky decisions that can lead to failure. It is hypothesized that as resources increase, the rate of change in success will decrease. Thus,

H2: The relationship between a firm's slack resources and its successful adoption of innovations follows over time a nonlinear path of S-shaped growth.

2.4.1.4 Marketing-R&D Integration

There is strong and consistent empirical evidence, applicable across both services and products and in both customer and industrial markets, that communication and cooperation between marketing and R&D enhances new product development success (Griffin & Hauser, 1996; Moenart & Souder, 1990). NPD projects that balance marketing and R&D inputs have higher rates of success (Cooper, 1984a, 1984b). Cross-functional integration reduces language, thought, and physical barriers. This enables more information to be communicated and utilized, increasing coordination and decision-making (Ruekert & Walker, 1987).

Similar predictions can be made regarding the integration of marketing and R&D and the successful adoption of innovations. Proliferation of an exchange of information about potential market demands allows R&D to better anticipate how an innovation adopted into the organization will facilitate the invention of new products. Likewise R&D can provide marketing personnel with information regarding internal technology progress that may provide solutions for customer demands. The inter-exchange of ideas between departments increases idea generation and knowledge assimilation. This creates a better understanding by both departments on how externally created innovations may be successfully utilized within the firm for new product invention.

"It has become generally accepted that complementary functions within the organization ought to be tightly intermeshed, recognizing that some amount of redundancy in expertise may be desirable to create what can be called cross-function absorptive capacities. Cross-function interfaces that affect organizational absorptive capacity and innovative performance include, for example, the relationships between corporate and divisional R&D labs or, more generally, the relationships among the R&D, design, manufacturing, and marketing functions (e.g., Mansfield, 1968: 86-88)" (Cohen & Levinthal, 1990, pg. 134).

Griffin & Hauser (1996) argued that marketing and R&D responsibilities in new product development are neither independent nor static; they cannot be analyzed separately. Responsibilities in both departments intermingle as new technological emerges, as customer needs change, as competitors offer new products, and as environments evolve. Thus,

H3: The greater the marketing-R&D integration, the more successful the adoption of catalytic innovations into the firm.

2.4.2 Outcomes of the Successful Adoption of Innovations

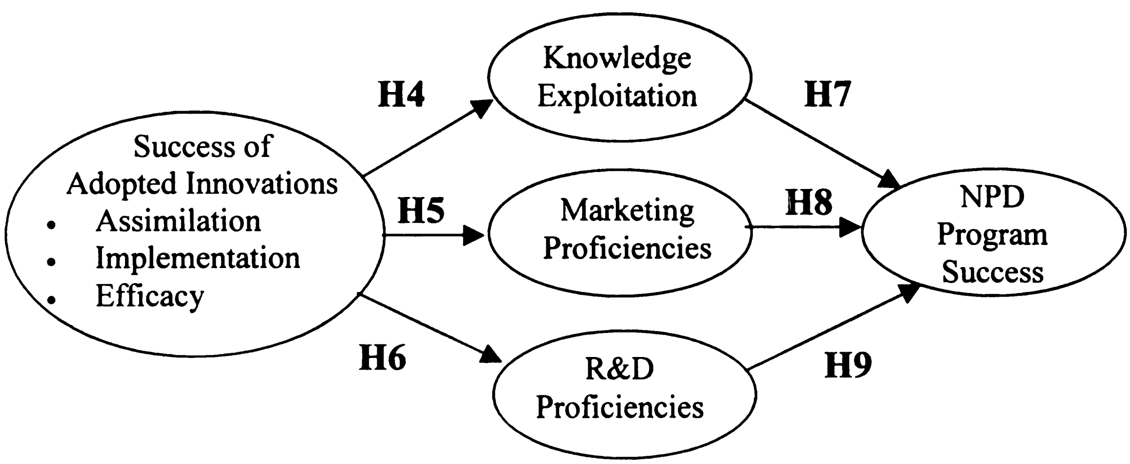
Extant literature has focused on how an innovation moves through stages in becoming a standard part of an organization (cf. Meyer & Goes, 1988; Pelz, 1983). Management and organizational behavior researchers have looked at how an innovation evolves as it assimilates into the organization for internal use (Leonard-Barton, 1988; Van de Ven & Rogers 1988; Van de Ven & Poole 1990). Reinvention (Rice & Rogers,

1980) is a common occurrence during implementation (Rogers, 1983, 1995; Tornatzky, et al., 1980). Van de Ven and Poole examined the innovation process and proposed a methodology that emphasizes the evolution of relationships among internal organizational ideas, people, transactions, and outcomes over time. These studies have all focused on the intra-organizational effects of post-adoption.

Rothwell & Gardiner (1988) introduced 'reinnovation' to explain the invention of incremental innovations. These researchers noted at least twelve patterns of redesign and reinnovation that occur throughout the new product development process from conceptualization to diffusion. Of these twelve patterns, four involve taking existing technology and improving upon it to invent new innovations: 'retrofitting', 'new generation', 'hybrid technologies', and 'radical technologies'. 'Retrofitting' involves the overhaul of existing product designs with new features and improvements whereas 'new generation' is a total redesign of an existing product. 'Hybrid technologies' upgrade existing products with new technologies whereas 'radical technologies' use new technology to introduce completely new products. The essence of these reinnovation processes is the utilization of one technology to invent a new product. Thus, technologies adopted by a firm are used in some manner in order to create a new product. It is not uncommon for one technology to act as a catalyst in the invention of a new technology (e.g., the Watt engine facilitated steamboat transit, smaller and faster semiconductors spurred laptop inventions, and lasers are now being used as 'scalpels' in heart surgery).

Yet, new product researchers know very little about how the adoption of innovations affects the new product development process over time. As previously noted, the infusion effects of innovations on the firm's new product development process are an under-developed area of research. This dissertation looked at the effect of the successful adoption of innovations on the firm's ability to exploit knowledge (H4), to build on marketing proficiencies (H5), and to build on R&D proficiencies (H6). Predictions regarding these hypotheses are described in this next section. Figure 2.3 delineates this sub-section of the model.

Figure 2.3 Infusion Effects from the Successful Adoption of Technological Innovations



2.4.2.1 Knowledge Exploitation as an Outcome

The firm's ability to evaluate, implement, and assimilate knowledge for commercial success is of strategic importance to the innovating organization (Grant, 1996; Cohen & Levinthal, 1990). This ability is frequently modeled as competitive advantage (Burgelman, 1990; Senge, 1990). Quinn (1992) proposed that knowledge based tangibles such as know-how, design expertise, and marketing insights largely determine the competitive advantage of most products. In these studies, knowledge is considered an asset.

However, knowledge can also be considered as a process (Nonaka & Takeuchi, 1995; Li and Calantone, 1998; Leonard-Barton, 1995). Nonaka and Takeuchi present a dynamic model for the creation of new knowledge starting with tacit knowledge that becomes embedded within an innovation, ending with the reabsorption of new knowledge into the organization from the development process. They describe this as a 'spiral of knowledge creation'. Li and Calantone distinguish between market knowledge and market knowledge competence. Market knowledge competence encompasses the processes that generate and integrate market knowledge (an asset) into a new product. This concept can apply to all types of knowledge competence.

Knowledge exploitation is a related but distinct concept from knowledge competence. Knowledge exploitation is the utilization of knowledge competence. Knowledge exploitation has been defined as "the use and development of things already known" (Levinthal & March, 1993, pg.105). The "essence of exploitation is the refinement and extension of existing competences, technologies, and paradigms" (March, 1991, pg. 85). Catalytic innovations that are successfully adopted by the firm bring with them new technologies and new ideas that can lead to the future development of new inventions. These new technologies and ideas increase the knowledge competence of the firm. If this knowledge is exploited, new applications from existing knowledge components will emerge (Kogut & Zander, 1992). How well a firm exploits the knowledge gained from the adoption of new innovations is a prediction of its success in

the new product development process. The greater the firm's success at assimilating new innovations into the firm, the more knowledge exists that can be exploited by the firm.

However, limitations exist on the firm's ability to exploit knowledge. A firm's carrying capacity will be reached, imposing constraints on future exploitation efforts. Human, capital and R&D resources are limited, as are knowledge compentences and managerial skills. Knowledge acquisition and exploitation are limited by these constraints. Additionally, it is possible for the firm to adopt too many innovations. Too many competing projects can result in all projects receiving little attention. Thus,

H4: The relationship between a firm's successful adoption of innovations and its knowledge exploitation follows over time a nonlinear path of S-shaped growth.

2.4.2.2 Marketing & R&D Proficiencies as Outcomes

It is expected that the successful adoption of an innovation will increase the overall marketing and R&D proficiencies of the firm. It is hypothesized that information collected during the decision making process of adopting innovations can lead to an increase in market and R&D knowledge. "The greater the technical knowledge resources, the more easily can new technical ideas be understood and procedures for their development and implementation be attained" (Dewar & Dutton, 1986 pg. 1431). The firm's carrying capacity (limitations on employee skill sets, education, managerial demands, etc.) will set limits on the growth in proficiencies. Thus,

H5: The relationship between a firm's successful adoption of innovations and marketing proficiencies in the new product development process follows over time a nonlinear path of S-shaped growth.

H6: The relationship between a firm's successful adoption of innovations and R&D proficiencies in the new product development process follows over time a nonlinear path of S-shaped growth.

2.4.3 Antecedents to NP Program Success

Numerous studies have been conducted regarding the antecedents to new product program success (Montoya-Weiss & Calantone, 1994; Brown & Eisenhardt, 1995; Cooper & Kleinschmidt, 1995). In this model of new product development as a complex system, three potential antecedents were tested, knowledge exploitation (H7), marketing proficiencies (H8) and R&D proficiencies (H9), Figure 2.3.

New product success has been accounted for in many ways (Griffin & Page, 1993; 1996). They report that firms and academics use over 75 distinct measures of product development success. Since the unit of analysis in this dissertation is the division, success was determined on a program level. Because different divisions have different product development strategies (Miles & Snow 1978), it is important to measure a division's success in growth, efficiency and effectiveness of the new product development program, and financial performance (Griffin & Page, 1996). The actual measures to be used will be delineated in Chapter 3 of this dissertation.

2.4.3.1 Knowledge Exploitation as an Antecedent

Drucker (1985) traces a firm's competence in new product development to its processes of generating knowledge about its customers and competitors and integrating such knowledge with technology. The greater its ability to utilize the knowledge generated, the greater the success in the NPD process. Leonard-Barton (1992) termed this ability as a firm's core capability. "[Core] capabilities continually spawn new products and processes because so much creative power is focused on identifying new opportunities to apply the accumulated knowledge base" (pg. 118).

Knowledge exploitation can be viewed as a core capability of the firm. Core capabilities differentiate a company strategically. It is hypothesized that a firm that exploits knowledge innovates new products with greater success. However, all core capabilities "simultaneously enhance and inhibit development" (Leonard-Barton, 1992, pg. 112). Core capabilities can result in core rigidities. Core rigidities evolve as knowledge exploitation causes firms to build capabilities in one specific area. Technical and managerial systems, skills and knowledge sets (assets), and values become ingrained to the firm. Firms become 'locked-in' to the old technologies and patterns of development activities. Thus, the cumulativeness and path dependencies of new product development can lead to technological, organizational, and institutional boundary limitations (Cohen & Levinthal, 1990; Alange, et al., 1998).

To break the path dependency of core rigidities in new product development, companies need to unlearn, or abandon earlier practices and behaviors that were found necessary, or even crucial, in other development projects. "An organization that engages exclusively in exploitation will ordinarily suffer from its obsolescence. The basic problem confronting an organization is to engage in sufficient exploration to ensure its current viability, and at the same time, to devote enough energy to exploitation to ensure its [future] viability" (Levinthal & March, 1993, pg. 105). Some organizations are able to use new projects as agents of renewal and organization-wide learning (Leonard-Barton, 1992), although most firms find this very difficult. It usually takes an environmental jolt (Meyer, 1982) or catastrophe (Bak, 1996) to move a firm off its self-reinforcing path of reliance upon tried and true technology onto a path of exploring and exploiting riskier technology. "One of the central findings of complexity theory is that robust (dynamic) systems evolve toward the balance between order (the pull of exploitation) and disorder (the pull of exploration) ..." (Lewin, et al., 1999, pg. 540).

Thus, it is hypothesized that over time firms that utilize their knowledge competence (exploitation of knowledge) will increase the success of their new product development projects. However, knowledge exploitation may begin to cause complacency in the firm's new product development process, negatively affecting new product success until an environmental jolt or catastrophe causes the firm to re-evaluate its knowledge exploitation behavior. This will result in an adjustment in knowledge exploitation over time. Thus,

H7: The relationship between a firm's knowledge exploitation and new product development program success follows over time a nonlinear path of S-shaped growth.

2.4.3.2 Market Proficiencies as an Antecedent

Marketing and R&D proficiencies have been empirically linked to the success of new products (Montoya-Weiss & Calantone, 1994). Cooper (1979) identified the notion of maximizing proficiencies in NPD activities rather than just undertaking the activities noted as key drivers of NPD success. Using a meta-analysis of forty-seven firms, Montoya-Weiss & Calantone (1994) found that proficiency in market related and technological activities are key determinants for driving new product success.

As early as 1956, Carter & Williams noted that marketing proficiencies are associated with technically progressive firms. Likewise, Kuczmarski (1988) found that skill at marketing activities is potentially critical for ensuring the success of new products. Thus, building marketing proficiencies are essential for ensuring NP success. Marketing activities requiring proficiency include customer orientation, competitive monitoring, program development, as well as launch activities. Thus,

H8: The greater the marketing proficiencies, the greater the success of the firm's new product development program.

2.4.3.3 R&D Proficiencies as an Antecedent

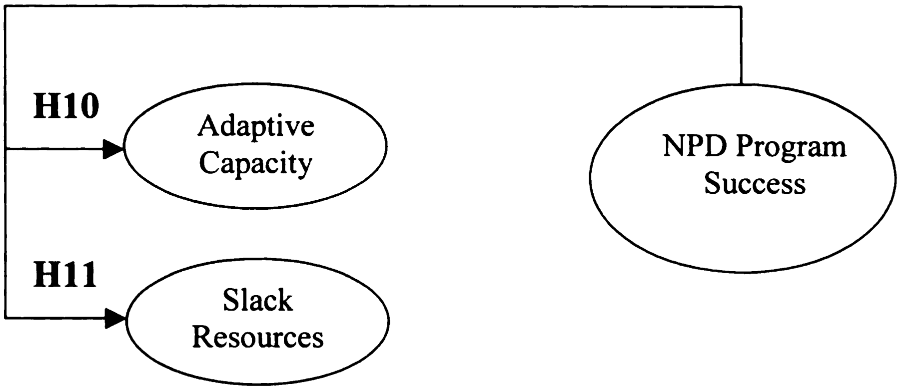
Quality of execution of technological activities - the actual physical development, product testing, trial production, and production start-up - has been linked to new product development program performance (Cooper, 1979; Cooper & Kleinschmidt, 1995). R&D strength has been noted as a major determinant of new product advantage (Li & Calantone, 1998). Day (1994) considered R&D strength a major internal capability and suggested that strong R&D provides a technological base critical to new product development. Technical activities requiring competence can include the R&D process, testing of the product, trial production, and production startup. Thus,

H9: The greater the R&D proficiencies, the greater the success of the firm's new product development program.

2.4.4 The Feedback Loop

The feedback loop as detailed in Figure 2.4 models the relationship between the success of the new product development program as an antecedent to the firm's adaptive capacity (H10) and slack resources (H11). Since this dissertation models the new product development process over time, it is necessary to determine the effects of program success on future development projects. The feedback loop modeled here looks specifically at slack resources and adaptive capacity over time.

Figure 2.4 Feedback Loop



2.4.4.1 New Product Program Success as an Antecedent

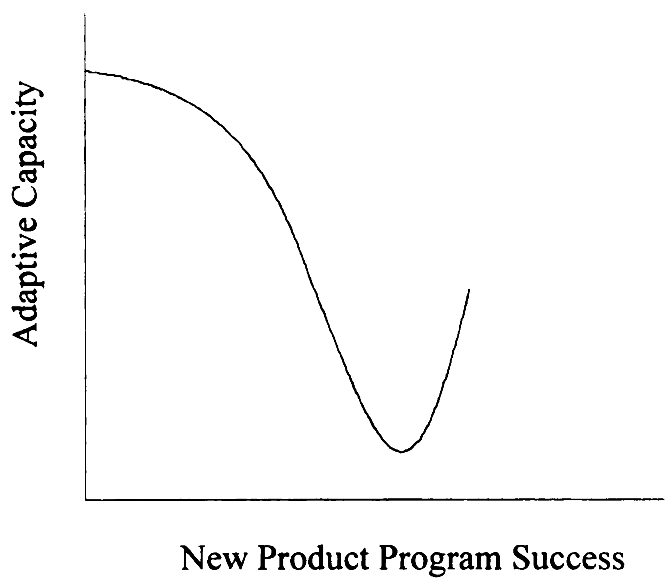
A firm's success can be its demise. This phenomenon has been called core rigidities (Leonard-Barton, 1995), stale in the saddle (Miller, 1991), or the 'Icarus paradox' Miller (1990). Successful firms can experience downward trajectories because their "victories and ...strengths...seduce them into the excesses that cause their downfall. Success leads to specialization and exaggeration to confidence and complacency, to dogma and ritual" (Miller 1990, pg.3). Technologically based companies can move from being pioneering entrepreneurs to 'escapists' where the focus on inventiveness becomes an unproductive pursuit of technology for its own sake (Miller, 1990).

Leonard-Barton (1995) reasoned that core rigidities form because attacking the rigidities "means undermining the current economic foundations of the firm – cannibalizing current product lines, making obsolete current knowledge bases and skills, lessening the values of current assets" (pg. 34). The politics of power and organization behavioral routines that become ingrained also contribute to the strength of core rigidities. The inertia of current practice can overwhelm concerted efforts to change a firm' strategy (Dougherty & Hardy, 1996; Hannan & Freeman, 1984; Johnson, 1988). These dependences on the status quo result in the decrease in a firm's absorptive capacity, its flexibility, and its marketing and R&D orientations, and hence its adaptive capacity.

Sustained success in a firm's established new product development program can lead to the Icarus paradox (Miller, 1990). However, an environmental jolt, internal or external (Meyer, 1982), or catastrophe, or even intelligent management can cause the firm to recognize the destructiveness of core rigidities and put a concerted effort back on building core capabilities. Over time, this leads to a negative relationship between new product program success and adaptive capacity (Figure 2.4). Thus,

H10: The relationship between a firm's new product development program success and its adaptive capacity follows over time a nonlinear path of inverted S-shaped growth.

Figure 2.5 Predicted Relationship H10



As previously noted, a firm's goals will determine how it accounts for success in the new product development program. It can rate success based on profits, market share, number of new products launched, etc. Regardless of the firm's method of determining success, greater slack resources result from greater success of new products. Griffin and Page (1996) found that Prospectors[6] determine new product program success through the growth derived from the program. One measure of success Prospectors use is 'degree today's products lead to future opportunities' (Griffin & Page, 1996, pg. 490). If a firm believes that today's products will lead to new products, it will allocate the resources necessary for evaluating future technologies that may spur new technologies. Even if financial slack resources are not readily available, growing firms will frequently obtain venture capital or other entrepreneurial funding for future new product development. Thus, financial success alone is not necessary to increase slack resources. As long as the firm continues to have the successes it predicts from the new product program, slack resources will usually be made available.

However, all resources are limited no matter how much wealth or potential success a firm has. Most firms will put a cap on the resources available for any single function within the firm. Additionally, Dougherty & Hardy (1996) found that in mature organizations, resources do not flow smoothly to new product projects, particularly where prevailing practices supported established activities. Thus,

H11: The relationship between a firm's new products program success and slack resources follows over time a nonlinear path of S-shaped growth.

[6] 'Prospector firms 'value being first with new products, markets and technologies even though not all efforts prove to be profitable' (Griffin & Page, 1996, pg. 482).

2.4.5 Hypotheses Summarized

Table 2.1 summarizes the hypotheses that were tested in this dissertation. The methodology used to test these hypotheses is presented in Chapter 3.

Table 2.1 Hypotheses

H1:	The relationship between a firm's adaptive capacity and its successful adoption of innovations follows over time a nonlinear path of S-shaped growth.
H2:	The relationship between a firm's slack resources and its successful adoption of innovations follows over time a nonlinear path of S-shaped growth.
H3:	The greater the marketing-R&D integration, the more successful the adoption of innovations into the firm.
H4:	The relationship between a firm's successful adoption of innovations and its knowledge exploitation follows over time a nonlinear path of S-shaped growth.
H5:	The relationship between a firm's successful adoption of innovations and marketing proficiencies in the new product development process follows over time a nonlinear path of S-shaped growth.
H6:	The relationship between a firm's successful adoption of innovations and R&D proficiencies in the new product development process follows over time a nonlinear path of S-shaped growth.
H7:	The relationship between a firm's knowledge exploitation and new product development program success follows over time a nonlinear path of S-shaped growth.
H8:	The greater the marketing proficiencies, the greater the success of the firm's new product development program.
H9:	The greater the R&D proficiencies, the greater the success of the firm's new product development program.
H10:	The relationship between a firm's new product development program success and its adaptive capacity follows over time a nonlinear path of inverted S-shaped growth.
H11:	The relationship between a firm's new products program success and slack resources follows over time a nonlinear path of S-shaped growth.

CHAPTER 3

OVERVIEW OF METHODOLGY

3.1 Chapter Summary

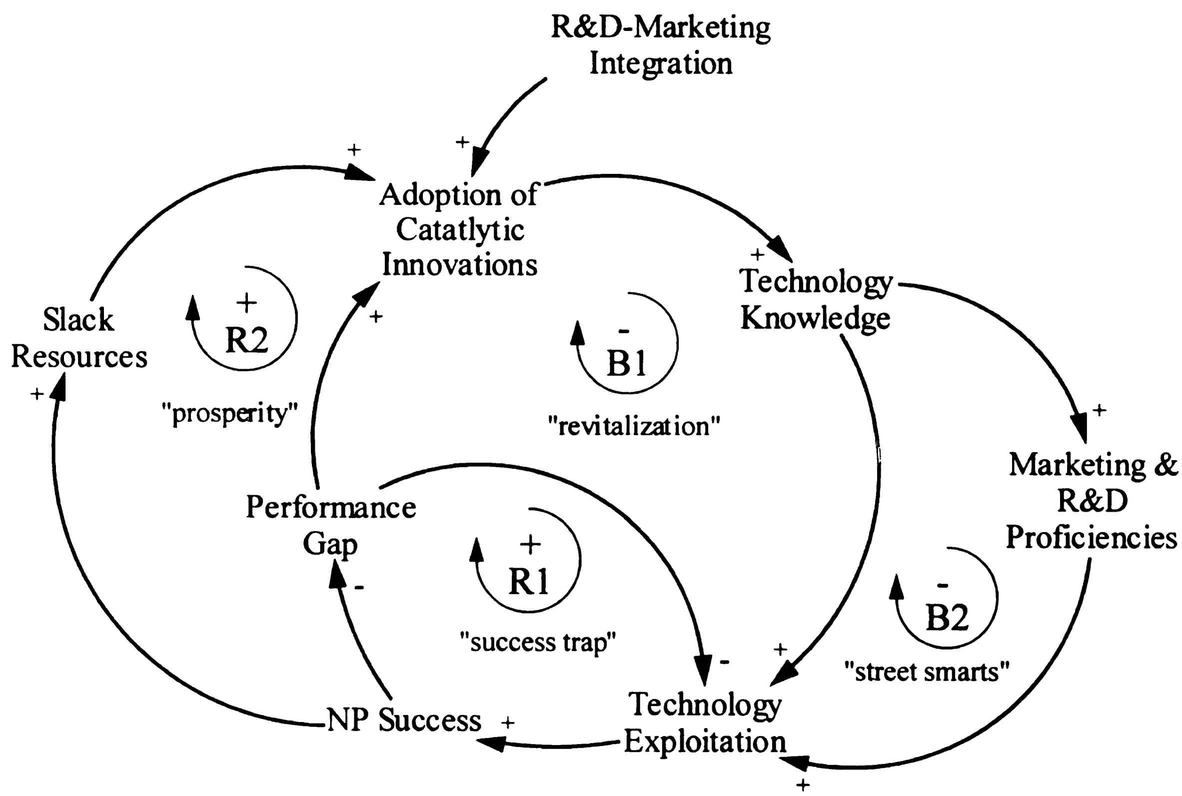
The hypotheses delineated in Chapter 2 were tested in two studies. Study 1 utilized a case study for data collection for a system dynamics model and study 2 utilized a longitudinal survey for data input to a structural equation model (SEM). In study 1, two case studies were used to identify the analytical relationships between constructs and to determine starting values for system dynamics modeling, which uses computer simulations to evaluate the interaction effects of nonlinear relationships. This method allowed testing of the hypotheses in a controlled setting and for modeling the feedback process. Additionally, field support for the predicted underlying theoretical relationships between factors described in Chapters 1 and 2 provided validity for the structural equation model to be tested in study 2.

In study 2, the data collected from the longitudinal study was analyzed using a growth curve model in structural equation modeling. Empirical data collection allowed for external validation of the hypotheses. The nonlinearities, with respect to time, of the relationships between constructs were the major focus of study 2.

3.2 Study 1 - Case Study & System Dynamics Simulation

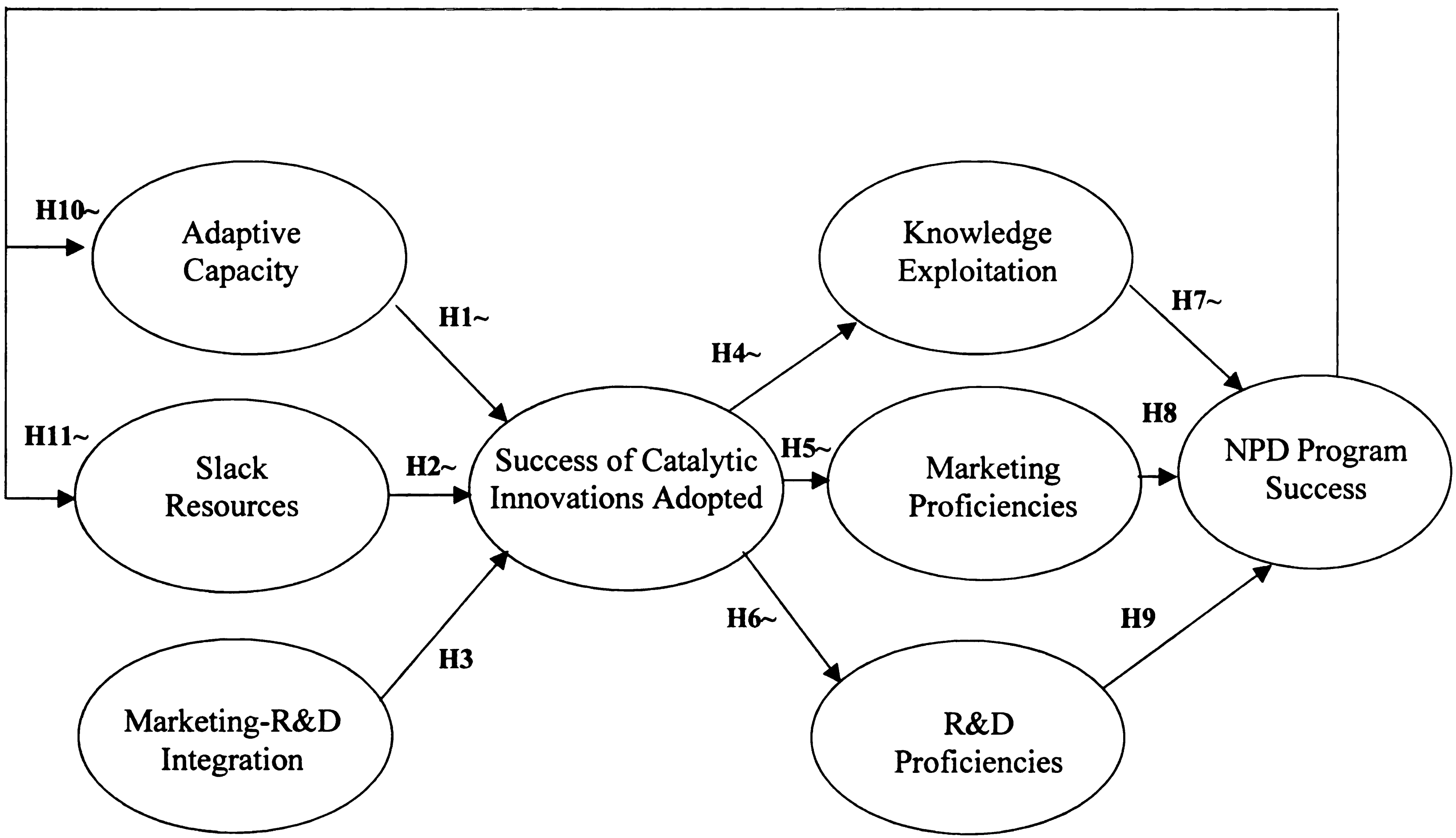
The intent of the case study was twofold: (1) to provide both qualitative and quantitative data for input into the system dynamics model, which is summarized in Figure 3.1 and further detailed in Chapter 4, and (2) to provide validity to the structural equation model, which is shown in Figure 3.2.

Figure 3.1 System Dynamics General Framework



Notes: Arrows represent causal relationships with direction noted as a (+) or (-). Loops labeled R indicate a reinforcing (+) feedback. Loops indicated with B, indicate balancing (-) feedback.

Figure 3.2 Full Structural Model



The exploratory nature of the case study facilitated identification of the functional forms of relationships that occur between the variables over time, both under normal and extreme conditions. The case study also allowed collection of quantitative data that was used as starting values for the system dynamics model.

Since no previously known empirical research had been conducted on the infusion effects of technological innovations on the success of the new product program process prior to this dissertation, the case studies provided a better understanding of this phenomenon. Identifying the characteristics of catalytic innovations through discussions with industry experts prior to the longitudinal survey increased the potential for obtaining content validity. The case study data collection techniques and system dynamics simulation techniques are described in the section below.

3.2.1 Case Study Data Collection

Creswell (1998) suggests that five different traditions of qualitative inquiry and research design exist - biography, phenomenology, grounded theory, enthnography, and case studies. He advocates that each method has distinct uses and each should be approached uniquely. "Case study is useful for studying a bounded system such as a process, activity, event, program or multiple individuals" (pg. 112). In this dissertation, the case study approach was used to evaluate the new product development process of a single technology firm. This phase of the study followed the framework of Eisenhardt (1989) for conducting inductive research. Although a priori specification of constructs is not standard in case studies, it can help shape the initial design of theory-building research and has frequently been used in building theory in the new product development research (Colarelli-O'Connor, 1998; Leonard-Barton, 1988). When constructs are found to be significant, researchers then have "a firmer empirical grounding for the emergent theory" (Bourgeois & Eisenhardt, 1988, pg. 536).

Pettigrew (1988) suggests that in selecting cases to be studied, researchers should choose cases that are extreme situations but are likely to extend the emergent theory. The first firm studied in study 1 is a small electronics company specializing in radio frequency power supplies for the semiconductor industry (employees = 75). This company is one of the seventy subsidiaries owned by a private corporation headquartered in New Jersey. For the fiscal year 2000, this company was rated the top earning (ROI) of all the seventy subsidiaries owned by the parent. In order to remain competitive in a very volatile industry, 20-30% of annual revenues stemmed from new products introduced within the last year. Due to their successful focus on new products, this company provided an interesting case study for evaluating the effects of the adoption of technological innovations on the new product development process. The second firm studied involved in the welding industry. They are a smaller firm (employees = 25) and most of their revenues stem from existing products or incremental improvements to their current product line. This company has recently experienced several years with low profit margins.

In case studies it is important to obtain multiple sources of information in order to build a wholistic picture of the problem being studied. Yin and Campbell (1989) recommends six types of information gathering techniques: interviews, direct observations, archival records, documentation, participant observations, and physical artifacts. For this case study, four methods of data gathering were used - interviews, direct observations, archival records, and documentation. Table 3.1 summarizes these techniques, as they took place chronologically within this study.

Table 3.1 Data Gathering Methods for Case Studies

- Semi-structured interviews with key employees
- New product team meeting observations
- Group meeting with key employees
- Documentation review
- Archival data collection (as permitted)
- Follow-up interviews with key employees as needed

A preliminary study of three additional companies was conducted in the summer of 2000. In addition to CSAA previously mentioned in the introduction, engineers from Leapfrog, an electronic toys designer, and EDC BioSystems, a biomedical firm, provided insights into their company's unique NPD process. Each of the interviews lasted 1½ to 2 hours. Based on these interviews, an initial model of the infusion effects of technological innovations was refined to greater reflect the reality of the new product development processes used in industry.

In-depth studies of the two case firm's new product operations were conducted over a one-week time period. Interview questions for the semi-structured interviews are included in the Appendix. Semi-structured interviews were held with key employees including the president, vice president, marketing manager, and senior engineers from each company. Typical of technology-based firms, both case study firms are engineering driven companies where the marketing manager has a limited role in new product development activities. Marketing primarily oversees marketing communications activities such as advertising, trade shows, etc. The vice president, thus, addressed the major marketing issues pertaining to new product development activities (Workman, 1993).

After interviews with key employees at the first case study firm, a group session was conducted in order to reach group consensus on the new product development process and to clarify questions surfacing from the individual interviews. Observations during NP team meetings supplemented the data collected during interviews. Archival data and documentation was used as made available. Since both companies are privately owned, this data was limited. The qualitative and quantitative data collected was then used for setting the initial conditions in the simulation analysis.

3.2.2 System Dynamics Model Simulation Analyses

Simulation techniques for modeling dynamic nonlinear systems are common in studying organizational behavior (Morecroft & Sterman, 1994; Repenning, 2001; Sastry, 1997). System dynamics modeling is used for modeling feedback loops and overall interactions between nonlinear relationships. Sastry (1997) emphasizes that this type of simulation differs from other formal modeling techniques in several important ways. First, system dynamics highlights feedback processes or circular causal relationships in which variables influence and interact with each other. Second, behavioral decision making is explicitly represented in the model as decision-makers are bounded by rationality with imperfect information. Lastly, because system dynamics models approximate continuous-time processes, they can be used to explore the effects of time lags.

The purpose of using simulation in this dissertation was to test the emergent relationships between the constructs over several time frames. Additionally feedback loops can easily be modeled using this type of simulation. The model in Figure 3.1 was simulated using system dynamics modeling software. This type of simulation involves building mathematical equations of the relationships and testing them under various conditions. This method followed the guidelines set by Levine, et al., (1992). The stages involved are shown in Table 3.2 and discussed in the section below.

3.2.2.1 Conceptualization

The first step in system dynamics model construction is 'conceptualization'. This step includes formulating the questions to be answered, describing the behavior of the problem to be addressed, specifying a time frame and forming a causal diagram of variable relationships. A major intent of system dynamics modeling is to model realistic behaviors and to answer practical problems. The primary question, of course, addressed the effect of the infusion of technological innovations on the NPD program process. Firms actively seek ways to increase the success in their new product development programs. It was hypothesized that adopting innovations may be one means of driving NPD program success. The models previously discussed in Chapter 1 and 2 describe the behavior of the NPD program, which were evaluated to address the research questions proposed.

Figure 3.1 shows the causal diagram form of the model. It is predicted in this model that the successful adoption of technological innovations will positively influence the success of the NP program success (direction of relationships is shown with a + or – in the figure). This relationship is established by increasing the internal knowledge base of the firm from adopting new innovations, thereby increasing the firm's ability to exploit this newfound knowledge and to build its marketing and R&D proficiencies. Knowledge exploitation combined with greater proficiencies will then lead to greater NP program success.

The internal boundary of the model is defined by those activities endogenous to the NP program process. Activities and managerial decision making occurring outside the realm of the program process are exogenous to this model. The unit of analysis was the program level that includes all new product development projects undertaken by a division (or a firm) within the specified time frame (Repenning 2000).

3.2.2.2 Formulation

Every system dynamics model is characterized by state variables and rate variables. State variables (also called 'stocks') can be thought of as an 'inventory' of goods, and hence, are also called stock variables. Rate variables are continuously changing and are directly manipulatable. "... system dynamics distinguishes between state variables, ...and variables that represent rates of change [rate variables]...The distinction is important because state variables, which represent the properties of the organization that have been accumulated over the organization's history and characterize the system, can not be changed instantaneously" (Sastry 1997, pg. 240). Exogenous variables are the third type of variable in a system. These variables set the boundaries for the simulation model. The state, rate and exogenous variables will be further detailed in Chapter 4.

The next step in the 'formulation' stage is to develop a flow diagram of the model with its associated computer (mathematical) equations. This is followed by selecting 'reasonable parameter values' for initial starting values for the simulation. These steps cannot be completed until after collection of the qualitative and quantitative data from the case study. Interviews with the case study firms provide the insights necessary to develop the analytical models that are used in the simulation. The semi-structured interviews asked the respondents to describe the NP program process within their firm and to provide 'best estimates' for the initial settings for exogenous variables that were subsequently used in this study.

Asking respondents to 'graphically define' the relationships between variables over time is also common in system dynamics modeling data collection. This may require showing respondents nonlinear plots such as Figure 2.1 as well as a linear plot, which can be found in Figure A.1 in Appendix A. Respondents were than asked to graph the relationship between variables that they experienced within their firm. If respondents did not feel comfortable answering this type of question without considerable prompting, the question was dropped. A copy of the workbook developed for this part of the case study is in Appendix A.

3.2.2.3 Testing & Implementation

Levine, Van Sell and Rubin (1992) established three types of tests to verify system dynamics models: structural tests, behavioral tests, and policy tests. Structural tests include structural verification, parameter verification, dimensional consistency, and boundary adequacy. Behavioral tests include behavior reproduction, behavior prediction, behavior anomaly, surprise behavior, extreme policy, generalizability, and boundary sensitivity. Policy tests include changed behavior prediction, boundary commission, and system improvement.

The purpose of these tests is to determine the robustness of the model to normal and extreme situations and to ensure that no relevant paths have been omitted from the model nor have extraneous paths been added. Internal and external validity involves adding/deleting exogenous and endogenous variables to the model to determine their effects on the system (Janszen 2000). Sensitivity analyses (what-if scenarios) were also conducted on the model. This involves manipulating the rate and exogenous variables from normal to extreme values. This testing process did not change the constructs or the hypotheses that are to be tested in this dissertation.

The system dynamics software Vensim (2001) was utilized for running the simulation. Sterman (2000) advocates, "Without simulation, even the best conceptual models can only be tested and improved by relying on the learning of feedback through the real world... This feedback is very slow and rendered ineffective by dynamic complexity, time delays, inadequate and ambiguous feedback, poor reasoning skills, defensive actions, and the costs of experimentation. In these circumstances simulation becomes the only reliable way to test hypotheses and evaluate the likely effects of policies" (pg. 37). However, he stresses that system dynamics modeling is not a panacea; theoretical studies must be integrated with fieldwork. Thus, the second phase of this research included a longitudinal study with structural equation modeling analysis of the data.

Table 3.2 Stages of Model Construction (Levine, et al, 1992)

- Conceptualization
  - Definition of questions to be addressed
  - Description of problem behavior or reference mode
  - Specification of time horizon
  - Specification of the dynamic hypothesis in causal diagram form
- Formulation
  - Postulation of detailed structure-selecting state variables, rates, etc.
  - Developing a flow diagram and associated computer equations
  - Selecting reasonable parameter values from a knowledge of the system
- Testing
  - Testing the dynamic hypothesis: Do the basic proposed mechanisms generate and qualitatively reproduce the problem behavior?
  - Retesting of model assumptions: Does the model include import variables, and does it appear realistic enough for use?
- Implementation
  - Testing the sensitivity to perturbations: sensitivity to changes in variables and in loop structure
  - Testing responses to different policies
  - Translation of study insights to an accessible form

3.3 Study 2 - Longitudinal Study & Structural Equation Model

A longitudinal study provided quantitative data for input into the structural equation model (SEM), which is shown in Figure 3.2. The data collection techniques and the model are described in this section.

3.3.1 Longitudinal Study Data Collection

Data collection was conducted at three different points in time for the longitudinal study. The first data collection took place in July of 2001 followed with a second in December 2001, and the third in May 2002. The sample population was technological firms that had introduced new products to the marketplace within the last twelve months. Firms that have not introduced new products recently (i.e., start-ups) were excluded because they were not able to provide information on their new product program success at the time of the first data collection. Permission was obtained from the parent company of the two firms involved in the case studies. This company owns approximately 70 engineering driven manufacturing subsidiaries. These companies are involved in industries ranging from heat-treating equipment to structural foam products for funeral homes.

In anticipation of panel mortality in survey participants, three respondents from each of the companies were requested to complete the survey at each time frame; the President/CEO, Engineering Manager, and the Marketing Manger. Thus, even with personnel changes, the same survey was administered at the second and third data collection. This type of data collection where multiple groups (firms with multiple respondents) are measured on multiple variables in multiple waves is called doubly multivariate designs (Bijleveld, et. al 1998). In this dissertation the groups were not evaluated separately (between groups designs, which are popular in the social sciences) but instead, the focus was on the relationships between constructs over time.

The survey was pre-tested with at three firms prior to being administered in the field. Measures used and their sources are shown in the Appendix C. These measures are all on a seven-point Likert scale unless otherwise indicated. Five of the eight constructs utilized scales that had been previously reported upon in management and marketing literature. Measures for 'adaptive capacity' were taken from the extant literature on flexibility, absorptive capacity and marketing orientation. 'Knowledge exploitation' was based on the theoretical models of Cohen and Levinthal (1990) and March (1991). Measures for "Successful adoption of innovations" are based on Tornatzky & Klein (1982).

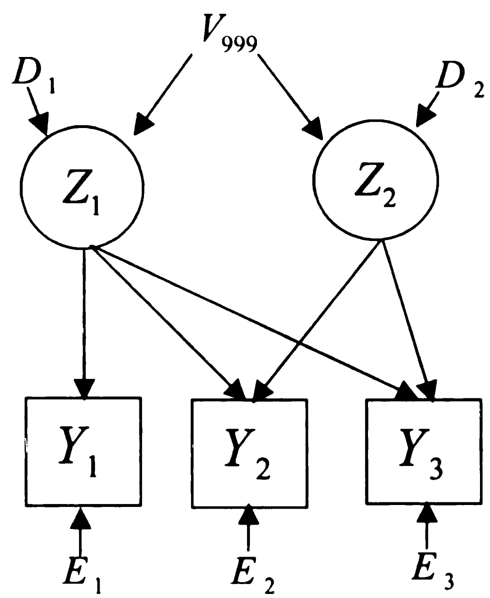
3.3.2 Structural Equation Modeling Analysis

When change is of interest in a study, longitudinal data collection is required. There are numerous ways in which to collect longitudinal data and evaluate it. The data collected in this dissertation was analyzed using EQS following the guidelines for structural equation modeling for linear growth models as suggested by Bijleveld, et al. (1998) and elaborated on by Duncan, et al. (1999). Linear growth curves postulate a theoretical structure for the variances and covariances of the factors as well as the means. In growth curve modeling, if a construct is plotted over time, "we see a curve that starts at an intercept and develops over time with either constant slope (linear growth) or with slopes that vary over time as well (curvilinear growth)" (pg. 248). Figure 3.3 graphically demonstrates this type of model. The latent vector Z_1 represents the intercept and the latent variable Z_2 represents the slope of the growth trajectory. The paths from V_{999} to Z_1

and Z_2 are equal to the means of the latent constructs. D_1 and D_2 represent the variances of the intercept and slope, respectively. Y_1-Y_3 represent the measure at each data collection; in this case there are three time periods. This type of model is explained in detail in Chapter 5.

The two step modeling approach suggested by Anderson and Gerbing (1988) where confirmatory factor analysis precedes the full structural model was utilized. Convergent validity, discriminant validity, and reliability were tested prior to running the full model.

Figure 3.3 Latent Growth Curve Model (Bijleveld, et al. 1998)



notes: Y1 = manifest variable at time=1, Y2=manifest variable at time=2, Y3 = manifest variable at time=3, Z1 = latent mean intercept; Z2 = latent mean slope, D1 = intercept variance, D2 = slope variance, V999 = EQS code for mean, E1-E3 error of manifest variables

3.4 Chapter Summary

This chapter has briefly summarized the two different methodologies that were used to test the model as presented in Chapter 2. The first study used system dynamics modeling to evaluate the NP development process as a system. The second study used a longitudinal panel study design to evaluate how the constructs change over time. In both of these studies time is an important factor, and as such, how the NP process evolves over time was an area of interest in this dissertation.

The remainder of this dissertation will cover details of conducting the two studies and the results of the studies. Chapter 4 details the system dynamics model and Chapter 5 details the linear growth curve models. Chapter 6 provides a summary of findings.

CHAPTER 4

RESEARCH METHOD - STUDY 1: SYSTEM DYNAMICS MODEL

4.1 Introduction

In study 1, system dynamics (SD) modeling was used to evaluate the effects of the adoption of innovations on the new product development process. SD modeling is based on the work of Forrester (1968) and was more recently formalized by Coyle (1996), Maani and Cavana (2000), and Sterman (2000). It combines information feedback theory and behavior decision theory in order to map an organization's operating policies, information flow, and decision-making processes (Morecroft, 1985; Sterman, 1987). By simulating real world behavior that may be difficult to capture in static models, the system dynamics approach focuses on how processes evolve over time and how policies might be changed to improve the firm's performance. Organizational structures and behaviors are evaluated through analysis of a combination of positive and negative feedback structures. Because it can approximate continuous time processes rather than discrete time periods, SD modeling can be used to explore the effects of time lags at work in decision-making as well as the resultant effects of the decision.

Moreover, in system dynamics, decisions and policies are conceptually differentiated. It would be fair to say that in the initial model building process, system dynamicists emphasize capturing the policies (decision rules) used in the situation being modeled (Forrester 1968; Forrester, 1994). Those policies can be conscious or unconscious, rational or irrational. Policies in the model are reflected by equations and table functions, both of which may represent nonlinear relationships. Decisions for actions and adjustments to changing conditions are based on those policies. Decisions, when made, are concrete applications of those policies or decision rules (Levine, 2002).

SD modeling has been used in several studies evaluating NPD programs processes (Black and Repenning, 2001; Milling, 1996; Repenning, 2001) and in organizational decision-making (Carroll, et al, 1994; Levine, et. al, 2001; Morecroft and Sterman, 1994; Sastry, 1997). For this study, Vensim, an off-the-shelf programming package by Ventana Systems (2001), was used to build the model of approximate differential equations that represent the dynamic changes occurring in a new product development program over time. The unit of analysis is the multi-project NPD program of technologically driven firms. The time unit of analysis is one quarter, which is a standard financial gauge as quarterly results are commonly reported, especially for public firms. A 20-year analysis, or 80 quarters, was selected to simulate the average length of time top managers may require to observe the long-term effects on the NPD program.

4.2 Case Studies

Because decisions and policies are represented explicitly, formulations should reflect the existing understanding of behavioral decision-making involved in the processes being modeled. To ensure that variables are meaningful and relationships observable, real world observations should inform the modeling as much as possible (Sastry, 1997; Sterman, 2000). Accordingly, the model in this study is based on case studies of two technologically driven firms, and is further supplemented with information from 55 technology-based firms from nine different countries. Both case study firms are technologically driven manufacturing companies, one in the semiconductor industry and the other in the induction welding industry. The semiconductor firm had experienced its best performance in about 10 years during the 2000-2001 fiscal year. The induction welding industry was struggling but had managed to make a profit in the 2000-2001 fiscal year after several previous years of being 'in the red'.

Extensive discussions over several months with the presidents and engineering managers of the two companies provided a foundation for modeling these firms' new product development programs and the decision-making criteria endogenous to the programs. Additional conversations took place with the top manager of several of the firms participating in the longitudinal study. Occasionally, a CEO/President would call me to "just let me know" about their current environment and "their specific NP process". These conversations were also used for insights into building the SD model. Important modifications and refinements to the model were undertaken throughout the course of these discussions. Appendix A shows the interview protocol for the case studies and a sample worksheet, which was used to help managers articulate the nonlinearities between construct relationships as hypothesized in Chapter 2.

As the SD model is based on a specific type of organization, a brief introduction to the two firms is warranted. The firms modeled in this study are engineering driven technologically oriented organizations. They have less than 100 employees of which 70% are manufacturing oriented and the remaining are engineering staff or top management. Little if any middle management exists, due to the small company size. The firms are between 20-30 years old and have annual revenues under $25 million. The NP program is not formalized with written documents but follows an 'unwritten' standard procedure. A CTO/VP Engineering or the president of the company heads the NP process. Competitors are typically well known. These firms would be considered more organic than mechanistic. Keeping this profile in mind will be important when the boundaries of the simulation are introduced in section 4.6. A summary description of these two companies is in Appendix A, Table A.1.

Based on information gathered during the case studies, two major refinements were made to the model as originally proposed in Chapter 1, 1.1. These modifications include: (1) adding 'technology knowledge acquisition' as a mediator between successful adoption of innovations and technology exploitation activities, and (2) modeling adaptive capacity as an amplifier/moderator. The first refinement concerns the role of knowledge in the NPD process. Madhavan and Grover (1998) argue that "from the idea-generation phase to the launch phase, the creation of new knowledge can be viewed as the central theme of the NPD process" (pg. 2). Nonaka (1994) supports this by suggesting that "innovation is a key form of organizational knowledge creation" (pg. 14). A primary reason for adopting innovations is to acquire knowledge currently not available in-house (Dewar and Dutton, 1986). The NPD manager's task is to manage the transition of knowledge embedded in adopted innovations to knowledge embodied as new products. Thus, technology knowledge acquisition itself plays a critical role in the NP process and is added as a mediator in the model, see Figure 4.1.

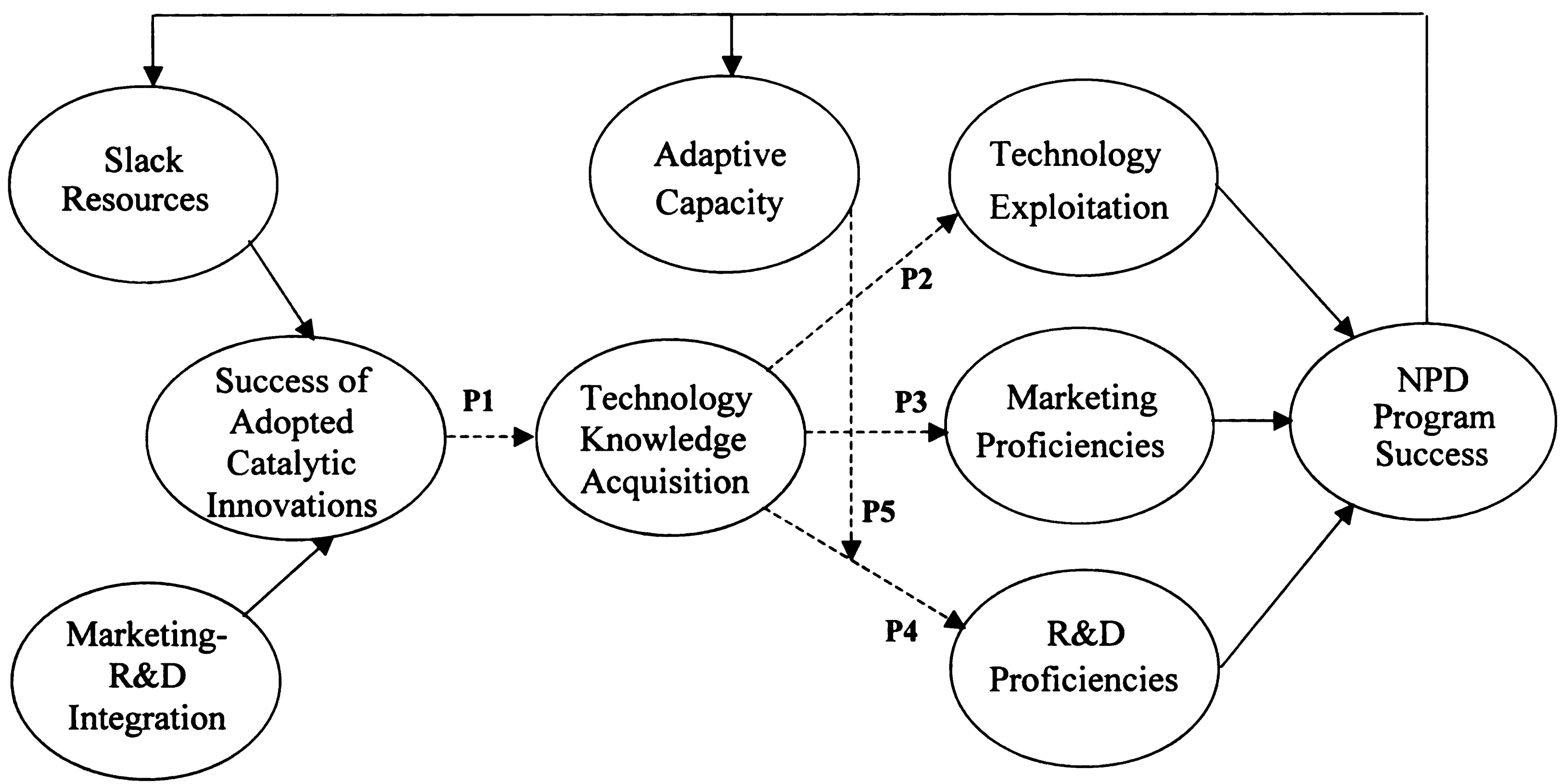
Discussions with representatives of the case study firms explicated the notion that exploitation is path-dependent upon exploration activities; a firm will not have the knowledge for exploitation (development) projects unless it has first conducted exploration (research) projects to develop the appropriate knowledge base. Knowledge gained from research activities feeds the knowledge base required in the development of new products. This knowledge base can be accessed by all participants in the new product process. In this revised model, gains in technology knowledge lead to increases in the firm's ability to build new products as well as in its marketing and R&D proficiencies.

The concept of adaptive capacity was discussed with the managers of the case study. These managers did not believe that a firm's adaptive capacity (firm's willingness, flexibility and ability to adapt to its environment) acted as an antecedent to the emergence of catalytic innovations during exploration activities. However, adaptive capacity did act as a moderator to the use of different knowledge stocks during the exploitation process. Not all knowledge is treated equally. The current environment can substantially influence the utilization of knowledge of different ages. Sometimes older, familiar practices and procedures are favored over newer knowledge.

An engineering manager from one of the case study firms explains; " If you can get away with using old [technology] knowledge, then do it. It is proven and reliable not only to the design engineers, but also to manufacturing and sales. If competition is putting on pressure, then you probably need to use new technology. It's purely an economic decision." Adaptive capacity may act as an amplifier[1] between knowledge acquisition and its utilization in the form of technology exploitation, marketing proficiencies, and R&D proficiencies. Thus, in Study 1, adaptive capacity is removed as an antecedent to adopted innovations and instead becomes an amplifier (see Figure 4.1).

[1] amplifiers in SD modeling are equivalent to moderators in the marketing literature.

Figure 4.1 SD Model with Paths Tested



notes: Added paths noted as dotted lines. P5 indicates Adaptive Capacity as an amplifier/moderator to P2, P3, and P4.

4.3 Overview of System Dynamics Model

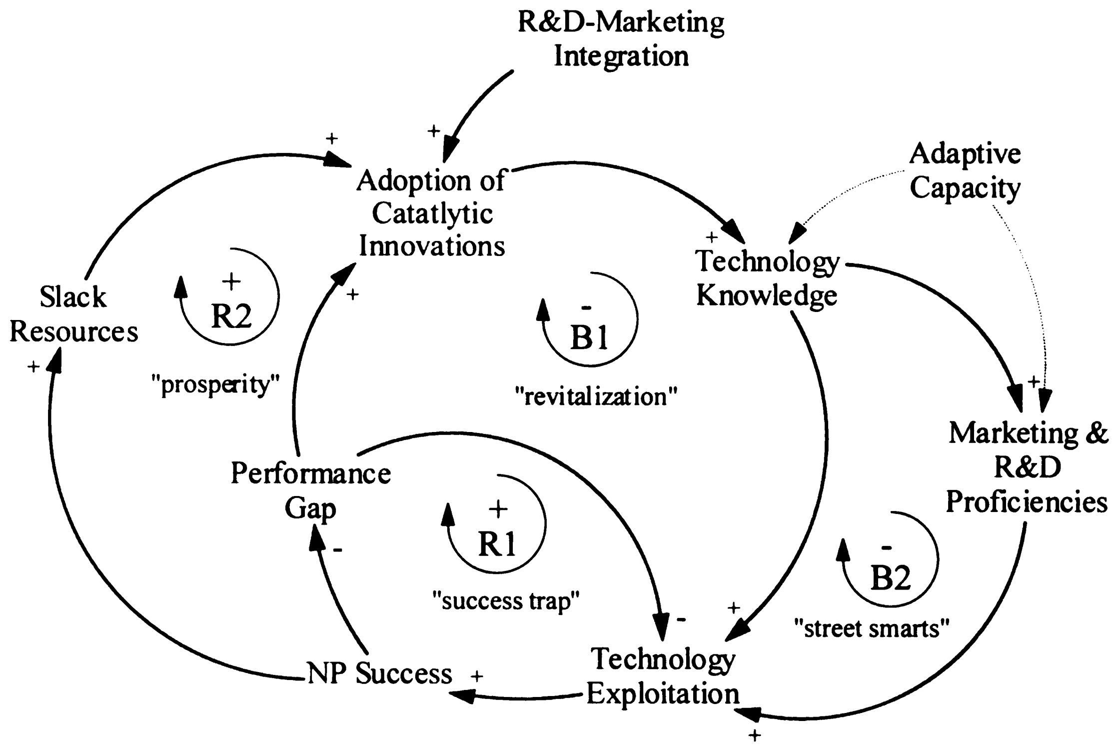
Figure 4.2 shows the basic premises of the SD model. The +/- notations on the arrows indicate the direction of the relationship between constructs in the model. This figure also illustrates the four primary feedback loops of interest in this study. Determining the polarity of a loop is important in order to trace the effect of a small change in a variable as it propagates around the loop. Starting from any variable, if the feedback effect reinforces the original change, it is a positive loop; if it opposes the original change, it is a negative loop. The polarity of the loop is the sign of the loop gain from the starting position, ∂x_n^O, until it returns to itself, ∂x_n^I (Sterman, 2000):

$$\textit{Polarity of loop} = SGN(\partial x_1^O / \partial x_1^I) = SGN[(\partial x_1^O / \partial x_n^I)(\partial x_n^O / \partial x_{n-1}^I)\ldots(\partial x_2^O / \partial x_1^I)] \quad (1.0)$$

It is common to name a loop to facilitate a general understanding of its role in the larger model. The first feedback loop, R1 "success trap", is reinforcing or positive. In a positive feedback process, a variable continually feeds upon itself to reinforce its own growth or its collapse. When this occurs, it is known as a "vicious cycle". In the loop R1, success in exploitation (development) results in a positive performance level, thus causing managers to focus less on exploration and more on the tried and true routes to maintaining profit levels – i.e., more exploitation activities. However, in this loop there is no opportunity to build new knowledge for developing innovative state-of-the-art products. Eventually, products become obsolete and the system can collapse upon itself. This models the phenomena described in Chapter 2 as a 'lock-in' to existing knowledge so that a 'lock-out' of old knowledge occurs.

The second reinforcing loop, R2 "prosperity", is singled out in Figure 4.3. It is positive controlling the amount of slack resources that become available to exploration

Figure 4.2: General Feedback Model



Notes: Arrows represent causal relationships with direction noted as a (+) or (-). Loops labeled R indicate a reinforcing (+) feedback. Loops indicated with B, indicate balancing (-) feedback.

Figure 4.3: "Prosperity" Feedback Loop

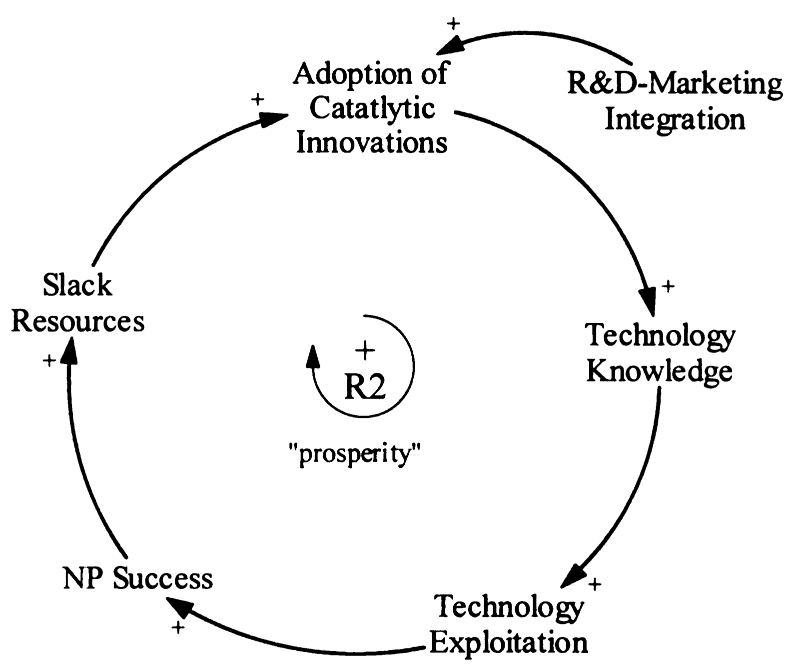


Figure 4.4: “Revitalization” Feedback Loop

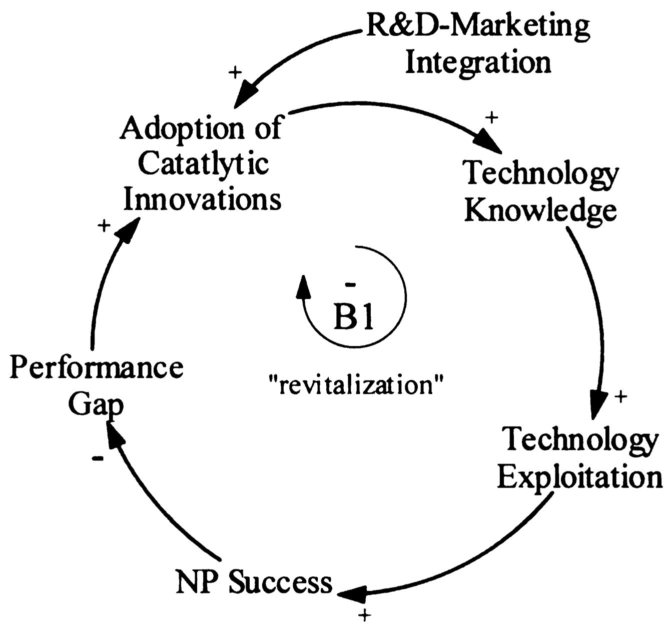
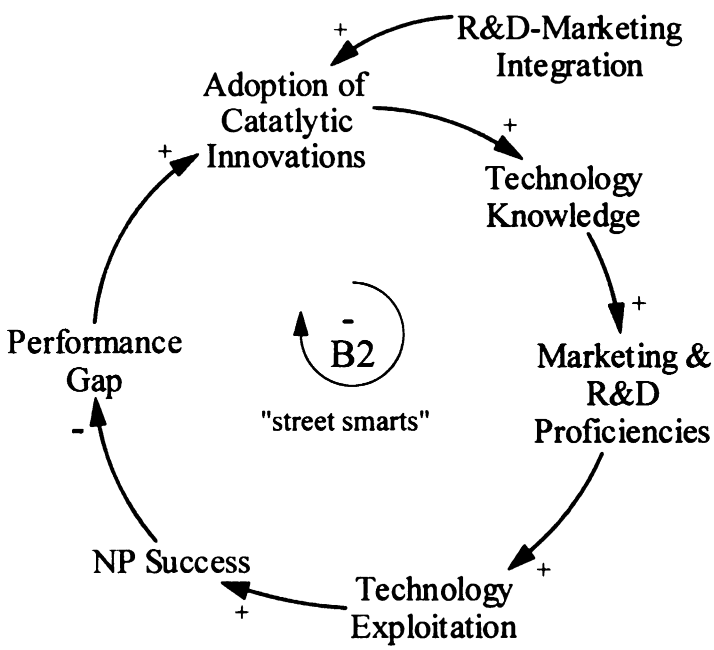


Figure 4.5 “Street Smarts” Feedback Loop



projects. In this loop, slack resources provide the means to adopt innovations that result in new technology knowledge. The new knowledge allows more new products to be invented (technology exploitation) feeding NP success that ultimately feedbacks to increase the stock of slack resources, thus slack resources feeds its own growth. In times of abundant slack resources (prosperity) the firm is able to undertake more exploration projects, even speculative ones, without jeopardizing overall program performance.

The first balancing (or negative) loop B1 is labeled “revitalization”. It is singled out in Figure 4.4. Negative feedback loops are characterized by goal-directed behavior. “Such terms as self-governing, self-regulating, self-equilibrating, homeostatic, or adaptive, all implying the presence of a goal, define negative feedback systems” (Goodman, 1974, pg. 37). In the system modeled here, the NPD program’s goal is to diminish any performance gap resulting from underachieving a target. The more target performance exceeds actual performance, or the greater the gap, the greater the focus is put on exploration activities through the adoption of catalytic innovations. A concentrated focus on exploration projects “revitalizes” the product portfolio with newer and better products, thus growing profits. Greater profits decrease the performance gap experienced in the previous time period, meeting the goal. This negative loop has the NPD program revitalizing the product portfolio when NP performance suffers.

The adoption of catalytic innovations also has the effect of increasing marketing and R&D proficiencies through the new knowledge acquired (feedback loop B2, "street smarts", which is singled out in Figure 4.5). Sufficient levels of marketing and R&D proficiencies are necessary to understand how to profitably invent and market the type of products that will be successful in the marketplace. These "street smarts" are an important part of any NPD program. The greater the proficiencies, the greater the ability exists to develop new products (technology exploitation) and the greater the NP success. This success closes any performance gap that had original driven the emphasis on innovation. Thus, a decrease in the focus on the adoption of innovations, or a negative feedback, results.

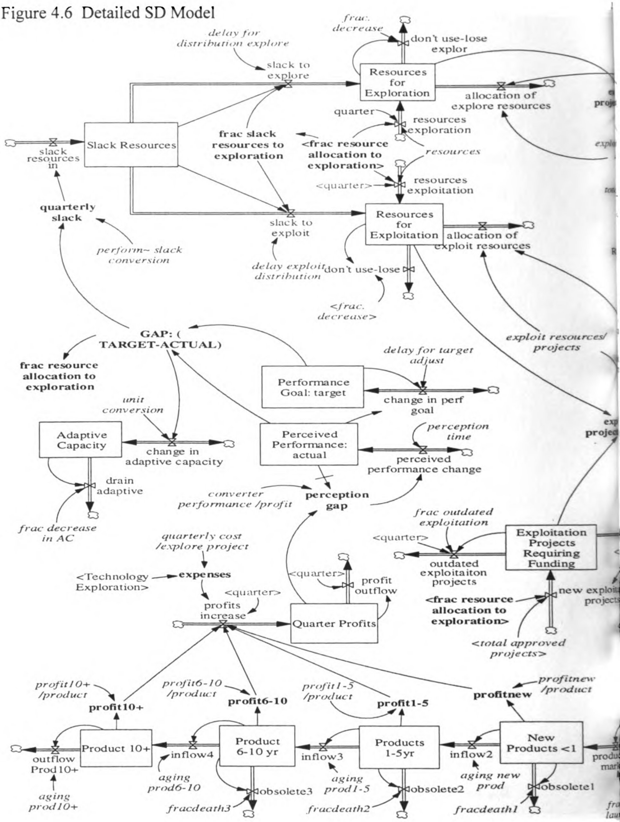
Figure 4.6 shows a more detailed view of the model in the form of a stock and flow diagram consistent with system dynamics models. In such diagrams, stocks (or states) are denoted by rectangles and represent properties or assets of the organization that have accumulated over time. Flows are symbolized by arrows with "valves" and represent action or activity within a system. Inflows to and outflows from the stock cause it to increase or decrease accordingly. That is the only way a stock can ever change. Moreover, flows are where the actions occur, but those actions are the results of the policies that have been captured by the model to represent how the actors will react to changes in the situation (Levine, 2002).

Flows, unlike stocks, may change instantaneously. For example, *Innovative Knowledge Stock* represents the technology knowledge of the NPD program accumulated (and lost) over the course of the simulated history of the organization. A firm builds a stock of technology knowledge through learning during research activities. Knowledge stocks can experience an "outflow" through a forgetting process (Ash and Smith-Daniels, 1999). Accordingly, a stock is a "snap shot" at a single point in time of its state resulting from inflows and outflows.

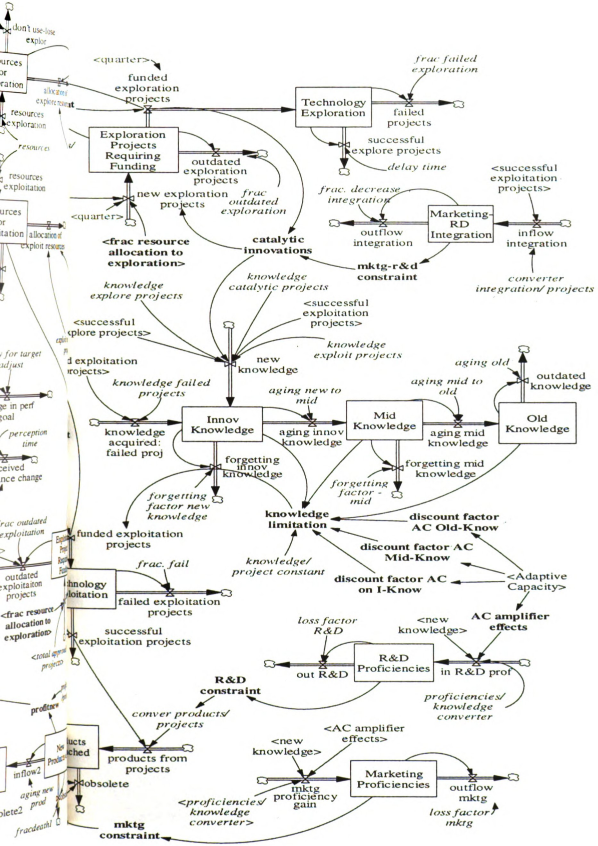
The NPD process can be examined by starting with the stock, Slack Resources. *Slack Resources, Resources to Exploration,* and *Resources to Exploitation* are allocated to *Exploration Projects* and *Exploitation Projects*. Successful exploration projects lead to 'successful adoption of catalytic innovations' and to increases in *Innovative Technology Knowledge Stock*, which provide the knowledge for development projects. This stock ages over time into *Mid-Knowledge* and *Old Knowledge*. The use of innovative or aging technology knowledge is moderated by the firm's A*daptive Capacity*. Knowledge is used to build *Marketing Proficiencies* and *R&D Proficiencies*. Successful exploitation projects lead to gains in *Products Launched*. The product portfolio ages over time resulting in varying profit levels for the aging products. Products sales result in gains to the *Quarterly Profit* stock. Profits lead to increases in *Slack Resources*, which may be used toward research and development projects, thus closing the loop in the NPD activities.

A third type of variable is used in SD models. 'Auxiliary' variables are neither stock nor flows but are intermediate concepts added to the model to add clarity. They are often broken out flow equations in order to allow a better understanding of the factors affecting the model. Three important auxiliary variables in this model should be noted: (1) 'fraction of resources allocated to exploration versus exploitation activities', $f_{R/D}$, (2) 'performance gap', G, and (3) 'catalytic innovations', P_c. The first two set the next quarter decision-making criteria, and the third is an outcome of undertaking exploration projects. Equations for the first two auxiliary variables are given in Appendix B.1.7.1 and the equation for catalytic innovations is in Appendix B.1.2.1. The remaining auxiliary used in the model are listed in Table B.3 and are briefly explained in Appendix B.2 which lists the Vensim code used in creating this model. Formulas for all the variables, stock, flow, and auxiliary as well as the constants, are in Appendix B.2.

Figure 4.6 Detailed SD Model



Legend: *italics-constants*; **bold-auxiliary variables**; stocks in boxes, flows represented by



boxes, flows repres

4.4 Central Assumptions

Four core assumptions are embodied in the model's structure. One central assumption of the model is that because the NPD program only has the ability to undertake a set number, *n*, of projects per quarter, it must decide whether to concentrate the NPD program efforts on exploration versus exploitation activities. This decision, the fraction of resources allocated to exploration (research) vs. exploitation (development), $f_{R/D}$, is a function of past performance (Lant, 1992):

$$f_{R/D} = f\,(\text{target performance} - \text{actual performance}) \tag{2.0}$$

A positive performance gap indicates that the NPD program is not meeting expectations. The more positive the performance gap, the greater the emphasis on exploration activities (see Figure 4.2, loop B1). A negative performance gap indicates that expectations are being exceeded, and thus the NPD program will concentrate on exploiting the existing knowledge base (Christensen, 1997; Miller, 1990). New exploration projects will be undertaken in order to try to close the gap. When NPD target performance equals actual performance, NPD managers will allocate equal proportions of resources to new exploration projects and new exploitation projects (Levinthal and March, 1981).

A related key assumption is that exploration projects are supplemented through slack resources. Slack represents resources, time, and energy that can be devoted to pursuing organizational goals which otherwise might have been channeled into other things. Levinthal and March (1981) further exemplifies, "slack is the difference between the potential performance of an organization and the performance actually received…It includes such manifest inefficiencies as over-designed equipment, over-qualified personnel, undiscovered improvements in current technology, and relaxed managerial control procedures" (p. 309). Organizational slack accumulates when performance exceeds the target.

The third key assumption is that resources available for research and development projects consist of 'budgeted' resources and 'slack' resources. Budgeted resources are assumed constant over time[2]. These are resources minimally required to maintain a NPD program. They are often budgeted by top management as an annual expense of running a NPD program. Even if slack resources are not available, budgeted resources allocated to the program will keep it functioning.

The fourth assumption concerns knowledge acquired through exploration and exploitation activities. It is assumed that exploration activities lead directly to increases in technology knowledge stock and indirectly to new products. As "exploration includes things captured by terms such as search, variation, risk-taking, experimentation, play, flexibility, discovery, innovation" (March 1991, pg. 71) exploration projects are riskier with more volatile outcomes. The payoffs from exploration must compensate for the uncertainty in the outcomes of these types of projects. The necessary result is significantly higher quantity of knowledge acquired from exploration projects compared to exploitation projects. The model also assumes that a small percentage (10% as modeled in this study[3]) of successful exploration projects result in catalytic innovations.

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[2] This assumption was based on input from several NP managers in addition to the managers involved in the case studies. A pool of budgeted resources are made available quarter. Additional resources, or 'slack' resources, which are a function of revenues, are added to the pool as they become available.

[3] As the concept of 'catalytic' innovations is new to the NP literature, this number is based on reports that 10% of NPD projects in firm portfolios are new-to-the-world (Griffin, 1997). This number has been consistent since originally being reported by the Booz Allen Hamilton study in 1982.

These catalytic innovations have two effects: (1) substantially increasing the knowledge base and (2) acting as a catalyst for new exploration projects to be undertaken.

4.5 Research Questions

In Study 1, the following questions were addressed. (1) How does the successful adoption of catalytic innovations affect NP program success? (2) How do changes in slack resources affect the successful adoption of catalytic innovations? (3) How do the allocation decisions between exploration and exploitation activities affect catalytic innovations? (4) What role does adaptive capacity play in the utilization of different types of knowledge in the innovation-centric organization? (5) How do changes in marketing-RD integration affect the success of the NP program?

A fundamental objective of SD modeling is to gain a greater understanding of how a firm's policies can affect its performance in various situations, particularly with respect to time. As product lines age and technology becomes obsolete, NP managers must make decisions on how to adjust the NP process. The role of catalytic innovations in creating policies to maximize NP program success is the major interest of Study 1.

The case studies confirm that adopted innovations are typically associated with a particular research project. The successful adoption of catalytic innovations is thus an outcome of a successful exploration project. However, exploration projects require funding. Cyert and March (1963) contend that slack resources are a necessary (but not sufficient) requirement for exploration activities. The existence of slack resources means that the organization can afford to absorb failures and to explore new ideas in advance of actual need (Rosner, 1968). "Slack encourages search activities that cannot be justified in terms of their expected return for the organization. They are initiated because of their attractiveness to some individuals or subunits, and tolerated because of the organization's current success in achieving targets" (Levinthal and March, 1981, p. 309). How the successful adoption of catalytic innovations changes with the increased or decreased flow of slack resources is a research question addressed in Study 1.

Because resources are limited, only a set number of projects can be undertaken in the typical NP program. Available resources must be allocated to exploration (research) and exploitation (development) activities. As modeled in Study 1, when targets are being met, resources are primarily allocated to exploitation activities. When targets are not being achieved, a greater focus is put on finding better, more innovative products through exploration activities. Firms must locate the proper balance point between new exploration projects and new exploitation projects. How these allocation decisions affect catalytic innovations was also explored in this study.

The acquisition of new knowledge itself does not guarantee the success of exploitation projects. As the case studies elucidated, not all technological knowledge is treated equal by the innovation-centric organization. At different phases of the NPD process, in different technological environments, and in different industries, the recency of knowledge acquisition can play a greater or lesser role. For example, highly intensive knowledge industries (i.e., biotechnical, pharmaceutical) may value newer knowledge of much greater importance to new product generation compared to older knowledge. Similarly, low intensity knowledge industries (i.e., food, packaged consumer products) can value older, well-known knowledge more than un-proven newer knowledge in new product development. Thus, knowledge is modeled as an aging chain (c.f. Sterman, 2000, chapter 13) whereby the age of the knowledge can have an impact on the projects undertaken by the firm.

Adaptive capacity is modeled as an amplifier to the aging knowledge stocks, to the marketing proficiencies, and R&D proficiencies. When adaptive capacity (AC) is positive, technologically oriented firms will put more value on new innovative technology. When AC is negative, a firm values older technology more. In a neutral state (AC = 0), innovative technology stock has the same value to the organization as aged technology knowledge stock. This is modeled as d_{AC}, a 'discount multiplier', or moderating factor. When AC is positive, old knowledge is discounted by d_{AC} and when AC is negative, newer knowledge is discounted by $1 - d_{AC}$.

A final policy that examined in Study 1 is the effect that marketing-RD Integration has on the successful adoption of catalytic innovations. Chapter 2 suggests there is a positive relationship between these two variables. However, a question of interest is: how important is this relationship to the dynamic NP process?

4.6 Research Design

Sterman (2000) stresses that the following questions must be asked of any model concerning robustness and sensitivity: (1) Are the policy recommendations sensitive to plausible variations in assumptions about parameters, aggregation (consistency between constructs), and model boundary? (2) Is the model robust in the face of extreme variations in input conditions or policies? and (3) Does the model exhibit surprise behaviors or anomalies? These questions are addressed through the research design.

In determining the research design, it is important to first define the model boundaries. As previously discussed, this study focuses on the effects of the adoption of innovations on the NPD process of technologically oriented organizations. The primary relationships modeled in this study examine the antecedents to catalytic innovations and their impact on NPD performance. Factors exogenous to the NPD program not modeled here include: competitive influences, environmental turbulence (both technological and marketing), rate of technology change, organizational structure, and firm ownership (public/private), to name a few. Several factors endogenous to the NPD process, but beyond the scope of this dissertation, are also outside of the model boundaries; e.g., availability of human capital, product portfolio mix, and cost of resources. The impact of these factors on the adoption of innovations is left for other studies.

Aggregation, or consistency between constructs, was tested by splitting the system into seven sub-modules: (1) resources, (2) exploration activities, (3) knowledge gain/lose, (4) exploitation activities, (5) proficiencies, (6) profits from products, and (7) performance gap and adaptive capacity. Each sub-model was tested alone and then coupled into the entire model. Additionally, these sub-models were also reconciled with managers of the case firms to verify the rationality of the decision rules as modeled[4]. These modules, along with the Vensim code used to model the differential equations, are shown in the Appendix B.

In order to test the robustness of the model, 32 simulations were run to determine the effects of changing conditions on the model. The first simulation establishes a base

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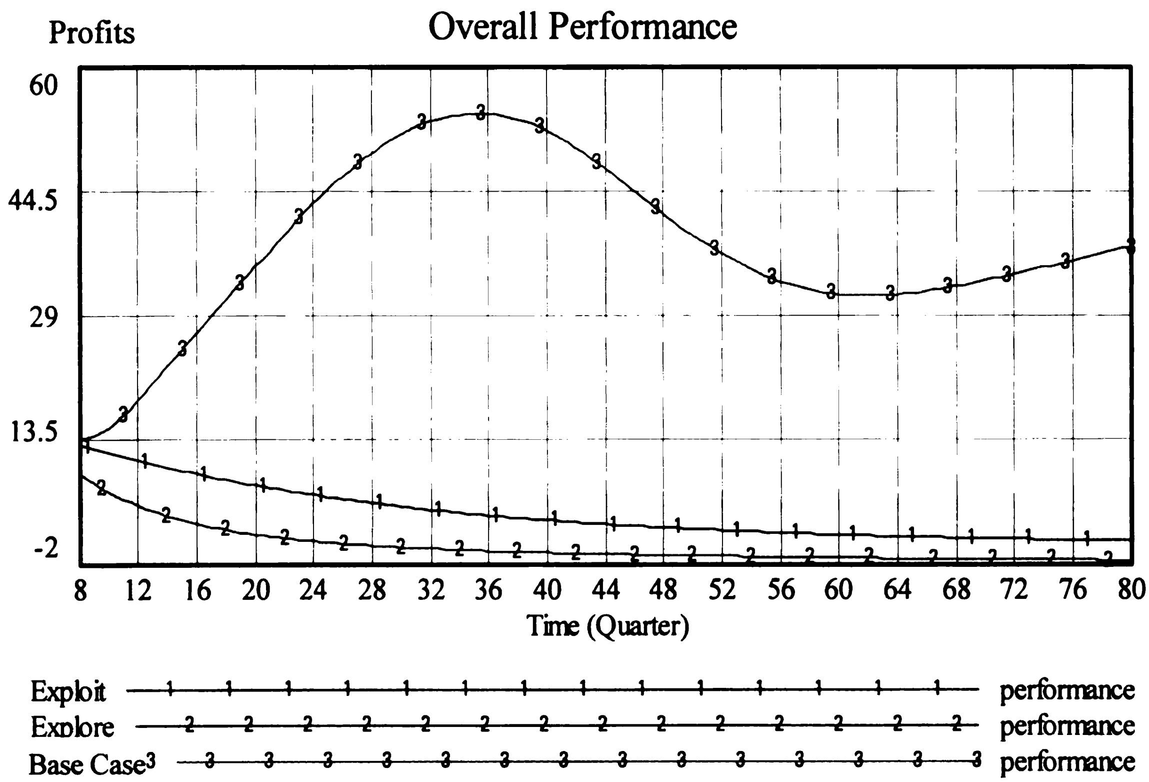
[4] Reconciliation of SD models with vested parties is one method of determining if the models accurately represent the phenomenon of interest (Levine, et al., 1992).

case to which all other runs are compared. Additionally, two test runs were conducted, the first simulating a NP program where only exploration activities occur ($f_{R/D} = 1$) and the second run where only exploitation activities occur ($f_{R/D} = 0$). March (1991) warns of the detriments of engaging exclusively in exploration or exploitation. "Adaptive systems that engage in exploration to the exclusion of exploitation are likely to find that they suffer the costs of experimentation without gaining many of its benefits. Conversely, systems that engage in exploitation to the exclusion of exploration are likely to find themselves trapped in sub optimal stable equilibria" (pg. 71). The base model was run under conditions of only exploration and then only exploitation activities. Figure 4.7 shows the overall performance results of the base case and the test runs. As can be seen in the graph, focusing solely on exploration or exploitation very quickly leads to a poor performing NP program.

Figure 4.7 Base Model Overall Performance & Test Runs



4.6.1 Simulations and Base Case

Parameters (constants) used in the models are shown in the Appendix, Table A.1. Initial starting values for the stock variables are identified in the Appendix, Table A.2. These values remain the same across all simulations. It must be noted that the parameters and starting values are based on input from the case studies. The case study firms were small engineering-driven, privately owned companies with informal NP programs.

Any unusual or unrecognized behaviors were resolved by working through each module of the system to determine the origination point of the anomaly. All discrepancies between the model behavior and the firms' NP program as described during the interviews were resolved. Many informal 'back and forth' discussions occurred with the managers of the case studies to clarify processes and decision-making rules. Initial conditions and constant values (see Table B.1, Appendix B) were also verified with the firm's managers. Extreme variations in initial conditions and decision-making rules (i.e. under what conditions to change from an exploitation to an exploration focus) were also tested. The starting values and other constants were varied to determine the sensitivity of the model to these changes. In any situation where the system was found to be highly sensitive to a change in a constant or decision rule, the constant (or rule) was set at the average value as reported by the case studies firms. For example, these firms on average undertake one new development project per engineer quarterly. Thus, the model used six new projects per quarter as one company had three engineers on staff and the other had ten engineers on staff. Starting values and constants may be significantly different for different types of organizations, and thus, the SD model would require revisions to reflect this type of firm. This limitation is further discussed in Chapter 6.

The thirty-two simulations were used to test the model for boundary conditions. They were run under 'high' and 'low' setting for five variables found to have the greatest impact on the successful adoption of catalytic innovations: slack resources, marketing-R&D integration, adaptive capacity, NP program success, and fraction of resources allocated to exploration activities. Thus, 32 simulations were conducted, which constitutes a 5 variable by 2 level research design (2^5). To set the high and low settings, constants were added to the functions used to model the phenomena. It is the constants themselves that are varied, not the mathematical functional relationship.

The stocks: technology knowledge exploitation, marketing proficiencies, and R&D proficiencies, were found to have little sensitivity on catalytic innovations. Accordingly, they were set high for all the simulations. The insensitivity of these constructs to the SD model will be discussed further in the results section of this chapter. It is important to note that 'insensitivity' does not mean lack of relationship.

High slack resources indicate that 100% of profits are allocated back into the NP program (SLKR = 1). High marketing-RD integration indicates that the interaction between the two departments occur on a regular basis (MRDI = 1), and high adaptive capacity (ACAP =1) indicates that the firm's past performance will determine its willingness to utilize new knowledge over older knowledge; dated knowledge becomes discounted. When NP program success is set as 'high' (NPPERF = 1), new products entering the marketplace are always profitable; competitive factors do not play a factor in the profitability of the firm. When the fraction of resources allocated to exploration activities is set high (FRAC = 1), it varies as a function of the performance gap as previously described.

When slack resources are set 'low', 50% of NP program profits are allocated back into the NP process (SLKR = 0.5). Low marketing-RD integration indicates that there is little interaction between R&D and marketing departments. It is set at 50% of the high level (MRDI = 0.5). Low adaptive capacity, or more accurately no adaptive capacity (ACAP = 0), indicates that the firm does not consider past performance in its decision on how to use its existing knowledge base. A low NP program success represents that the firm is only able to sell their products in the marketplace at ¼ of what they would be able to in a 'high' profitable environment although expenses remain the same (NPPERF = 0.25). When the fraction of resources allocated to exploration is modeled low, this indicates that 50% of slack resources are always allocated to exploration activities and 50% are allocated to exploitation activities (FRAC = 0.5). It is not a function of the performance gap as when modeled 'high'. These high and low settings were chosen based on discussions with the firms in the cases, one that was performing extremely well and the second that was struggling. In these analyses, the dependent variable was taken as the successful adoption of catalytic innovations, and thus it was not set as either high or low. Table 4.1 shows the settings for each run.

The base case represents the system in a 'typical' environment as defined by the case study firms. The base case was modeled with all high settings. It sets the perspective from which the remaining simulations are compared. Thus, a brief explanation is necessary to set this reference frame. In all the simulations a two-year equilibrium period (8 quarters) is set where resources are equally allocated between exploration and exploitation activities. After this point in time, the independent and dependent variables are allowed to vary. As can be seen in Figure 4.7 for the base case, from quarter 8 (Q8) to about Q36, performance is gradually increasing as the firm overachieves its goals. The abundance of slack resources is primarily allocated to exploitation activities as the firm is performing well with its current product line. After about Q36, the firm's ability to keep up its current rate of growth begins to erode. Subsequently, fewer slack resources become available and fewer projects can be undertaken. What limited slack resources are available are allocated to new exploration (adoption of innovation) projects. At approximately Q60, the rewards of these exploration activities are observed as new products enter the marketplace driving up performance again.

Table 4.1 Simulation Legend – Constants Settings (H = high, L = low)

Run	SLKR	MRDI	ACAP	NPPERF	FRAC
Base	H	H	H	H	H
2	H	H	H	H	L
3	H	H	H	L	H
4	H	H	L	H	H
5	H	L	H	H	H
6	H	L	L	L	L
7	H	L	L	L	H
8	H	L	H	L	H
9	H	L	L	H	H
10	H	H	L	L	L
11	H	H	H	L	L
12	H	L	H	L	L
13	H	H	L	H	L
14	L	H	H	H	H
15	L	H	H	H	L
16	L	H	H	H	H
17	L	H	L	H	H
18	L	H	L	H	L
19	L	H	L	L	L
20	H	H	H	H	H
21	H	H	H	H	H
22	H	H	H	H	H
23	L	L	L	L	L
24	L	L	L	L	H
25	L	L	L	H	L
26	L	L	H	L	L
27	L	L	L	H	H
28	L	L	H	H	L
29	L	L	H	L	H
30	H	L	L	H	L
31	H	H	L	L	H
32	H	L	H	H	L

Legend

SLKR:	Slack Resources Constant	High = 1	Low = 0.50
MRDI:	Marketing-R&D Integration Constant	High = 1	Low = 0.50
ACAP:	Adaptive Capacity Constant	High = 1	Low = 0.00
NPPERF:	New Product Performance Constant	High = 1	Low = 0.25
FRAC:	Fraction of Resources Allocated to Exploitation Project Constant	High = 1	Low = 0.50

4.6.1.1 Results of Simulation

The purpose of conducting the simulations was to observe how the model reacted under various conditions. First, surprise behavior and anomalies from the base case where checked. None were observed in these simulations. Secondly, ANOVAs were run to determine how the stocks themselves would vary under these different conditions. Mean values for the 80 time periods were calculated for each of the stocks of primary interest and subjected to the ANOVA analysis. The ANOVA results comparing the 32 simulations (31 + base case) are shown in Table 4.2.

Evaluating the effects of the various conditions on the successful adoption of catalytic innovations indicate three distinct groups of results. Group 1 (n = 10) has the lowest mean for the successful adoption of catalytic innovations. Group 1 has low levels on 3 or more out of the 5 constants that were allowed to vary. All the members of group 1 have low levels of Marketing-R&D integration. Eighty percent have low performance levels as a constraint.

In group 2 (n = 16) 75% of the group has high marketing-R&D integration. Sixty-two and ½% have low settings on slack resources and 62½ % have low settings on adaptive capacity. All the members of group 3 (n = 6) have high settings for both slack resources and NP program success. This is an expected result as slack resources are needed to undertake the adoption of innovations and slack resources are generally more available when NP program success is high. Although the influence of marketing-RD integration on the successful adoption of innovations may be an artifact of the programming of the SD model, the relationship is worth more investigation in future research.

Table 4.2 Means of Stock Variables From Simulations & Results of ANOVA Analyses

Run	CATALYT	SLACK	MKT-RD	ADPT CAP	KNOW	TECH EX	RDPROF	MKTPROF	NP PERF
6[1]	1.43	0.05	7.15	0.00	24.25	4.71	11.01	9.74	14.28
7[1]	1.43	0.08	6.99	0.00	24.58	4.66	11.16	9.89	14.12
8[1]	1.43	0.08	6.99	0.16	24.58	4.66	11.21	9.94	14.14
12[1]	1.43	0.05	7.15	0.16	24.25	4.71	11.02	9.78	14.29
22[1]	1.43	0.61	8.07	-0.51	24.34	5.12	10.92	9.64	15.55
23[1]	1.42	0.02	7.14	0.00	24.21	4.71	10.99	9.72	14.25
24[1]	1.42	0.04	6.96	0.00	24.53	4.64	11.14	9.87	14.07
26[1]	1.42	0.02	7.14	0.16	24.21	4.71	11.04	9.77	14.26
27[1]	1.43	0.61	8.07	0.00	24.35	5.11	11.02	9.75	15.56
29[1]	1.42	0.04	6.96	0.17	24.53	4.64	11.19	9.92	14.09
Group1 Mean	1.43	0.16	7.26	0.014	24.38	4.77	11.07	9.80	14.46
3[2]	1.48	0.08	6.99	0.16	24.64	4.66	11.23	9.96	14.15
10[2]	1.48	0.05	7.15	0.00	24.31	4.71	11.03	9.76	14.29
11[2]	1.48	0.05	7.15	0.16	24.31	4.71	11.08	9.81	14.30
14[2]	1.48	0.61	8.07	-0.51	24.41	5.12	10.95	9.67	15.57
15[2]	1.51	0.42	7.42	-0.51	24.85	4.84	11.14	9.86	14.69
16[2]	1.47	0.04	6.96	0.17	24.58	3.32	11.01	9.94	14.10
17[2]	1.48	0.61	8.07	0.00	24.42	5.12	11.05	9.78	15.57
18[2]	1.51	0.43	7.42	0.00	24.85	4.84	11.27	9.99	14.74

Table 4.2 (con't) Means of Stock Variables From Simulations & Results of ANOVA Analyses

Run	CATALYT	SLACK	MKT-RD	ADPT CAP	KNOW	TECH EX	RDPROF	MKTPROF	NP PERF
19 [2]	1.48	0.02	7.14	0.00	24.27	4.71	11.02	9.74	14.25
20 [2]	1.47	0.04	6.96	0.00	24.58	4.64	11.16	9.89	14.08
21 [2]	1.48	0.02	7.14	0.16	24.27	4.71	11.06	9.79	14.26
25 [2]	1.46	0.43	7.42	0.00	24.79	4.84	11.24	9.97	14.73
28 [2]	1.46	0.42	7.42	-0.51	24.79	4.84	11.11	9.84	14.68
30 [2]	1.53	1.06	7.85	0.00	25.70	5.05	11.64	10.37	15.60
31 [2]	1.48	0.08	6.99	0.00	24.64	4.66	11.18	9.91	14.13
32 [2]	1.52	1.04	7.84	-0.52	25.67	5.04	11.48	10.21	15.48
Group2 Mean	1.49	0.338	7.37	-0.875	24.69	4.74	11.16	9.91	14.66
Base[3]	1.62	1.81	9.96	-.585	28.47	5.88	12.13	11.55	18.44
2 [3]	1.56	1.04	7.84	-0.52	25.74	5.04	11.51	10.24	15.49
4 [3]	1.60	1.61	8.90	0.00	26.29	5.49	11.84	10.56	17.01
5 [3]	1.55	1.61	8.88	-0.52	26.14	5.50	11.66	10.38	16.93
9 [3]	1.54	1.60	8.90	0.00	26.19	5.49	11.79	10.52	16.99
13 [3]	1.56	1.06	7.86	0.00	25.78	5.05	11.67	10.40	15.61
Group3 Mean	1.59	1.45	8.72	-0.271	26.43	5.40	11.77	10.61	16.75
Grand Mean	1.48	0.48	7.56	-0.09	24.85	4.86	10.80	9.97	14.94

Superscript indicates group membership based on ANOVA, all p <0.0011 – Group 1 (n = 10); 2 – Group 2 (n = 16); 3 – Group 3 (n = 6)
Legend: CATALYT-catalytic innovations (auxiliary variable); SLACK – slack resources stock; MKT-R – marketing-R&D integration stock; ADPT CAP – adaptive capacity stock; KNOW – innovative knowledge stock TECH EX –technology exploitation stock; RDPROF- R&D proficiencies stock; MKTPROF – marketing proficiencies stock; NPPERF – New product < 1 stock

4.7 Results

This section reports on the five research questions posed in section 4.5. These questions were evaluated in two ways: (1) by evaluating the change trajectories of the constructs with respect to time and (2) by conducting sensitivity analyses to determine the impact on the dependent variable of interest by the change in an explanatory variable. Sensitivity testing is the process of changing the assumptions about the value of a constant set in the model and examining the resulting output for the impacts to this change. It is similar to the ANOVA analysis previously described except here the focus is on one explanatory variable. Hundreds of simulations with the constant varying over a range of values can automatically be performed using Monte Carlo simulations in Vensim. Confidence intervals show the spread of values that the stock takes from varying the constant. These sensitivity analyses are shown in Figures 4.9-10, 4.12, 4.14, 4.16-18, and 4.20. The different shadings in the graphs indicate 50-100% confidence intervals. The lightest center shading indicates the 50%CI and the outside bands 100%CI. The centerline running through the 50%CI represents the mean value at each time point of the Monte Carlo simulations. Each sensitivity analysis was run using 200 Monte Carlo simulations.

4.7.1 Research Questions Evaluated

To address the research questions, the base case was evaluated for its evolution with respect to time and the variables of interest. The following discussion uses the base case in each evaluation. The first research question looked to address what effect (if any) do the adoption of catalytic innovations have on NP program success. Figure 4.8 presents a viewpoint of how the auxiliary variable, adoption of catalytic innovations, and the stock variable, NP program success, change over time.[5] Curve 1 shows the change trajectory of catalytic innovations, and curve 2 shows the trajectory of the NP program performance with respect to time. By plotting both of these curves together, it can be seen how both variables change together. Figure 4.8 demonstrates that adopting catalytic innovations in moderation may increase NP program success. A decrease in NP program success is seen when catalytic innovations are high. This is not necessarily an effect of the catalytic innovation but more of an impact of the focus on exploration projects from which catalytic innovations emerge. A propensity toward exploration projects results in fewer exploitation projects, and hence, fewer new products are introduced to the market. More resources are also used in exploration projects. A research focus, as opposed to a development focus, and the resulting drain on slack resources leads to a decrease in NP program success. Too much of a research focus can hurt achieving optimal NP program success as shown in Figure 4.8. This type of oscillation in NP program success has been observed in numerous innovative companies such as Hewlett-Packard and 3M especially in the mid-1980s.

Figure 4.9 shows the sensitivity of catalytic innovations on NP program success. The peak indicates 100% of all adopted innovations are catalytic innovation representing maximum knowledge yield from adopting an innovation. The lowest curve indicates that no adopted innovations are catalytic; all innovations result in standard knowledge yield. The middle curve represents the mean from varying the catalytic innovations from all (100%) to none (0%). The 100% scenario assumes that every exploration project results in a catalytic innovation so that large knowledge gains are achievable through every

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[5] Note the two different scales along the y-axis, one for each variable. These numbers are representative of the relationship and should not be taken at face value.

exploration project. This new knowledge is then easily and cost effectively turned into new products. If this could be achieved, NP performance could be maximized.

Figure 4.10 shows the effect of changes in NP program success on the number of resulting catalytic innovations. These evaluations lend support for the theory proposed in Chapters 1 and 2 that the successful adoption of innovations can have a positive effect on NP program success. High NP program success can significantly increase catalytic innovations, whereas low NP program success leads to very few catalytic innovations. This is expected because high NP program success can result in excess slack resources, which can then be allocated to exploration projects.

Figure 4.8 Base Case NP Program Success & Catalytic Innovations

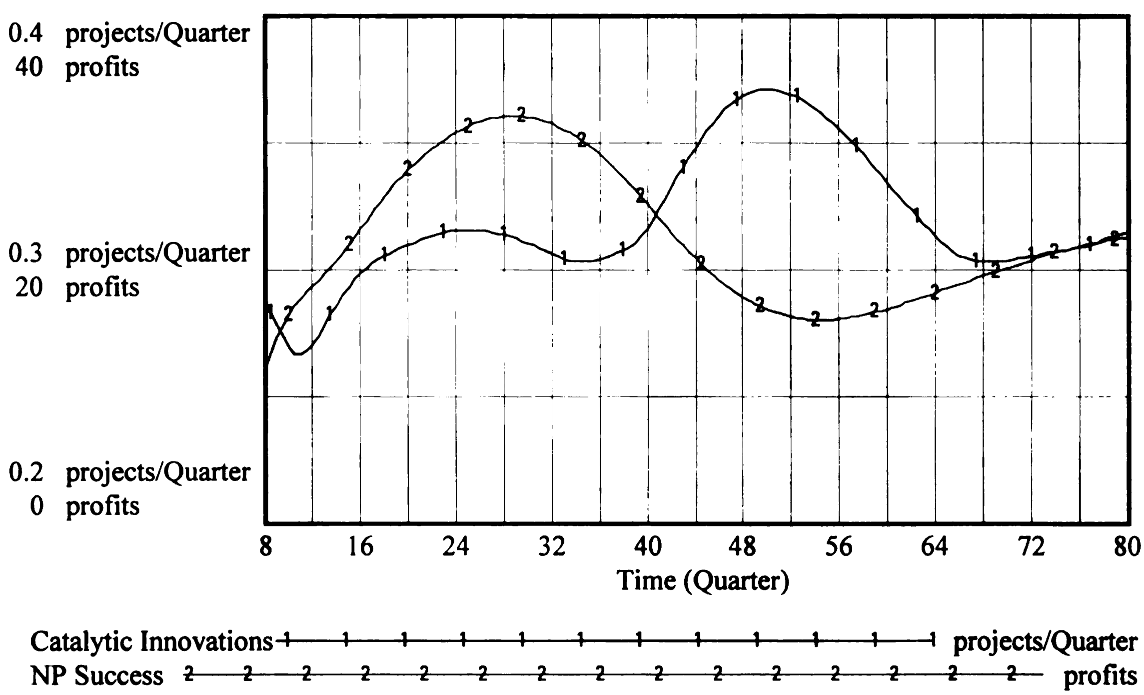


Figure 4.9 Sensitivity of NP Program Success to Changes in Catalytic Innovations

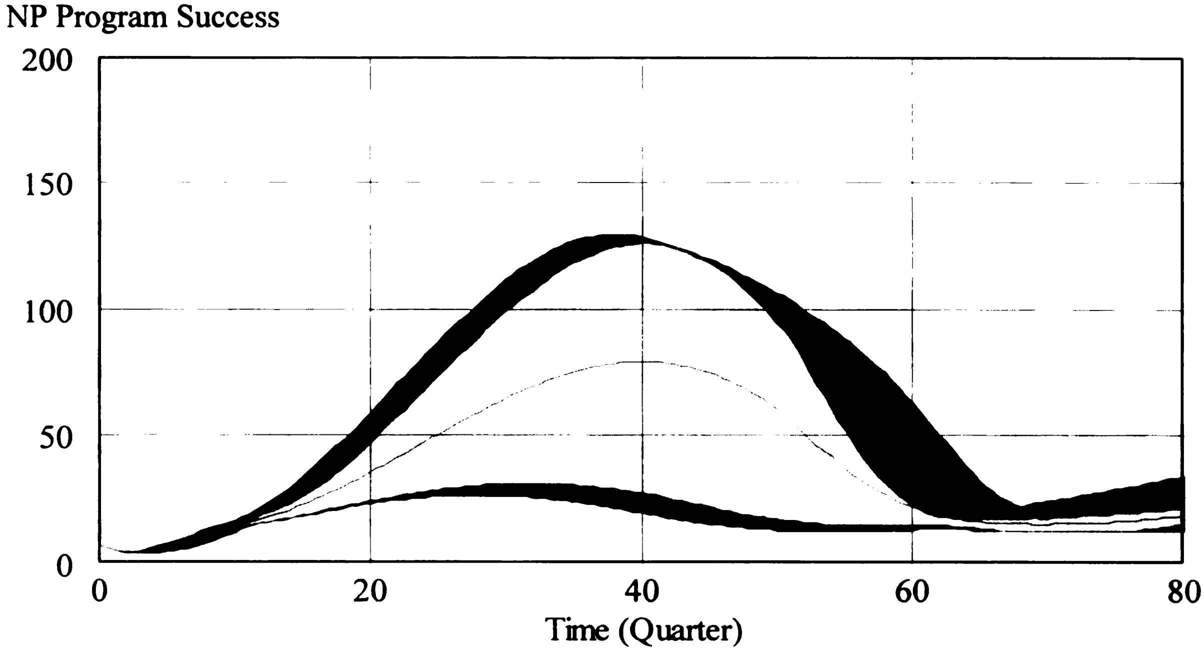
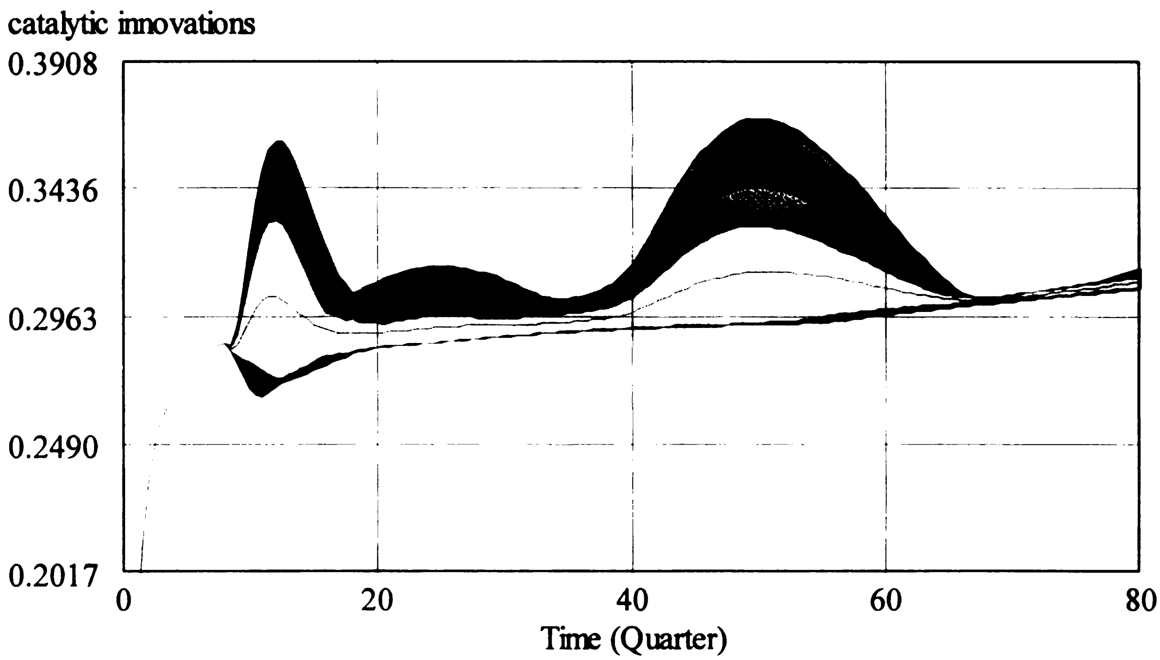


Figure 4.10 Sensitivity of Catalytic Innovations to Changes in NP Program Success



Question 2 of the research questions presented in this chapter asked how do changes in slack resources affect the successful adoption of catalytic innovations. As slack resources grow, more exploration and more exploitation activities can be undertaken. Slack resources fall to zero when actual performance falls short of the targeted performance. Slack resources are necessary for the emergence of catalytic innovations because they provide the funding for exploration activities, the vehicle by which catalytic innovations arrive. Yet, slack resources alone are not sufficient for ensuring the emergence of catalytic innovations. This is seen in how the adoption of catalytic innovations changes over time.

In Figure 4.11 from time=8 to approximately time=40, there is a slight increase in catalytic innovations when slack resources are high; however, from time 40 to approximately time=64, there is a significant increase when there are no slack resources. The failure to reach the targeted goal results in an increased focus on exploration projects. Starting at about time period 40, there is a shift in focus from exploitation activities to exploration activities because performance levels are not being met. Recall loop B1 (Figure 4.4) where the performance gap is positively related to an increase in the adoption of innovations – the greater the gap, the greater the focus on looking for new technologies. This results in a substantial increase in catalytic innovations. Thus, although slack resources have fallen to zero, a firm may still put a focus on adopting innovations in order to try to improve overall NP program success.

Figures 4.12 shows the sensitivity of catalytic innovations to changes in slack resources. Superimposing Figure 4.11 on 4.12 shows that catalytic innovations are not driven by the availability of slack resources but by the firm's need to close a performance gap through innovative new products. Catalytic innovations are found even when there are no slack resources available. This dual influence is shown in Figure 4.2 where both slack resources and the performance gap has positive effects on the adoption of catalytic innovations.

Question 3 focused on the relationship between allocation of resources and catalytic innovations. Figure 4.13 shows how percentage of resources allocated to exploration activities affects catalytic innovations. This figure demonstrates very well the dual influence on catalytic innovations; from 8Q to approximately 38Q less than 50% of resources are allocated to exploration projects yet a slight rise is occurring in catalytic innovations. This gain is from the abundance of slack resources during this time period as observed in Figure 4.11. After 38Q the number of catalytic innovations grows even higher because of the greater than 50% resource allocation to exploration projects.

Figure 4.14 shows the sensitivity of catalytic innovations to changes in resource allocation. By comparing Figures 4.12 and 4.14, it appears that catalytic innovations may be more sensitive to the lack of slack resources than to insufficient focus on research activities. Catalytic innovations are more sensitive to lack of slack resources (lowest valley at 0.2) compared to a reduction in resources allocated to exploration (lowest valley at approximately 0.265). However, catalytic innovations are more sensitive to resource allocation decisions when modeled high than when slack resources are modeled high.

Question four looked at the role of adaptive capacity as an amplifier to knowledge utilization. Adaptive capacity has been defined as a firm's willingness and flexibility to be open to new ideas. When adaptive capacity is low, the firm cannot (or will not) easily adapt to environmental changes. When it is high, it is open to making changes as its environment evolves. Figure 4.15 shows how adaptive capacity changes over time (curve 1) along with the number of technology exploitation projects undertaken (curve 2). As adaptive capacity dips, the number of exploitation projects undertaken increases. As adaptive capacity increases, the number of projects decreases.

Adaptive capacity was also modeled as an amplifier to marketing proficiencies (curve 3 in Figure 4.15) and R& D proficiencies (curve 4). Similar dampened effects are also seen with these two variables. However, Figures 4.16-18 show these variables are highly insensitive to adaptive capacity. Adaptive capacity does not appear to be a moderator to these variables.

Research question 5 asked how the changes in marketing-R&D integration affected the success of the NP program. The effect of marketing-RD integration on catalytic innovations appears to have no effect on the success of catalytic innovations (see Figure 4.19). This success is most likely an artifact of the model itself. As modeled, marketing-RD integration increases with each successful exploitation project but erodes slowly. Thus, it does not act as a limitation to the successful adoption of innovations; only the upside of the two departments interacting is seen. The sensitivity analysis in Figure 4.20 shows that catalytic innovations are only slightly affected with changes in marketing-RD integration. This model finds little conclusive support for the relationship between these two variables.

Figure 4.11 Base Case Slack Resources & Catalytic Innovations

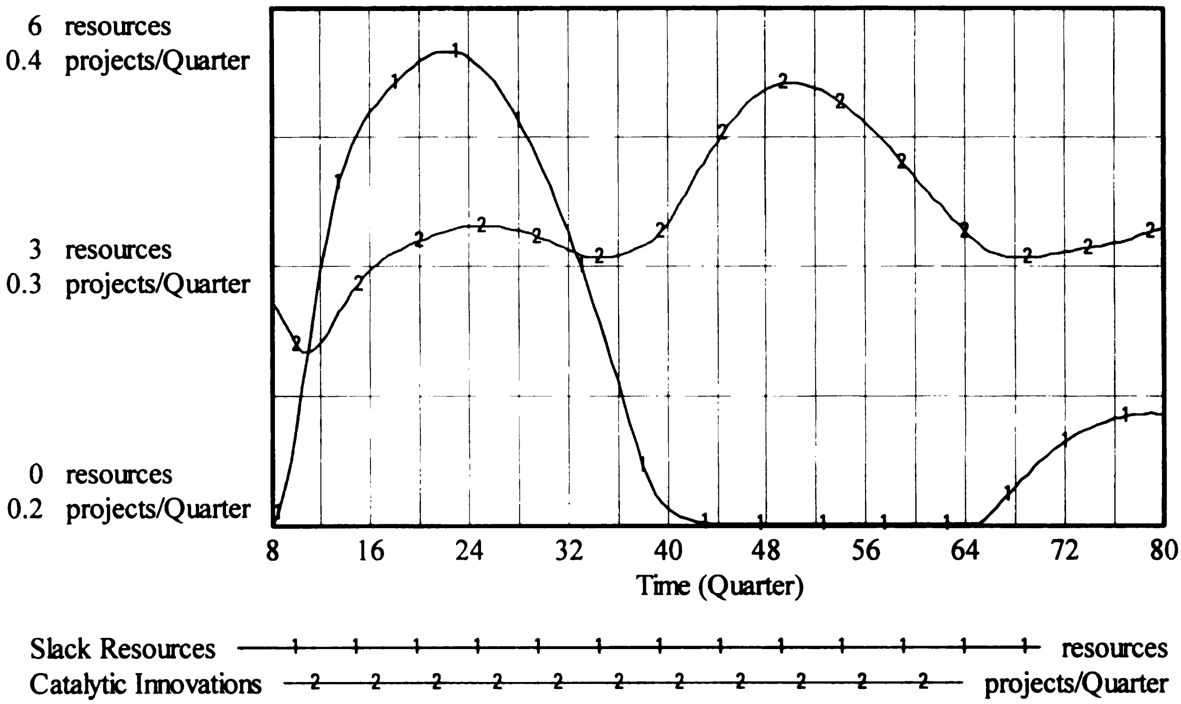


Figure 4.12 Sensitivity of Catalytic Innovations to Changes in Slack Resources

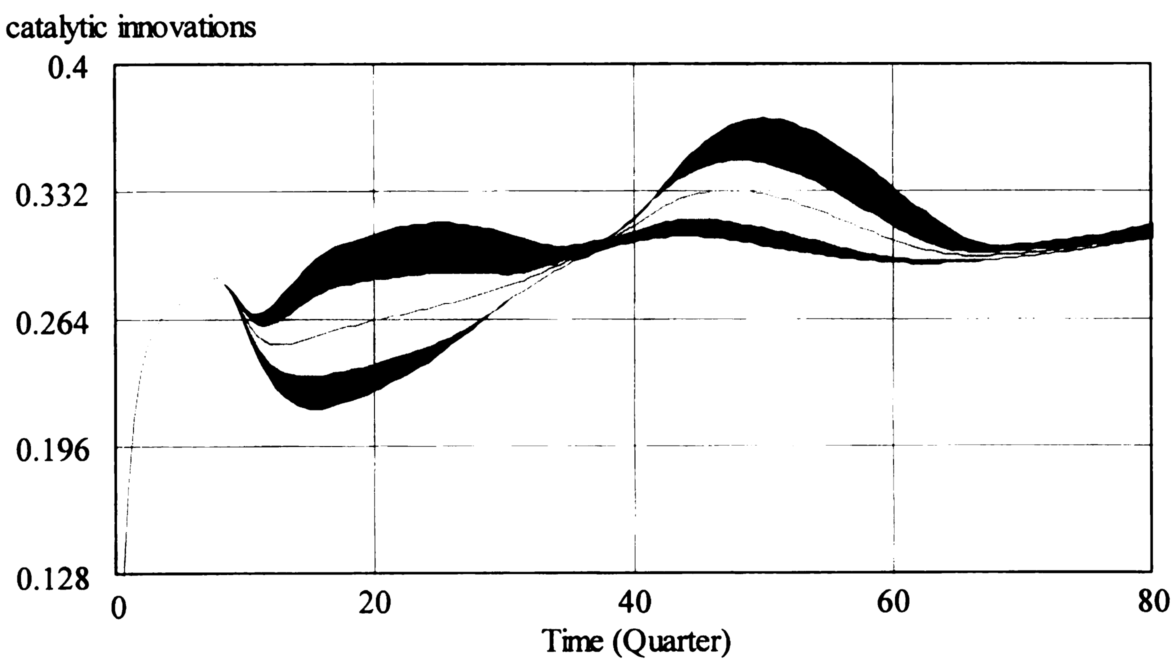


Figure 4.13 Base Case Fraction of Resources Allocated to Exploration Activities & Catalytic Innovations

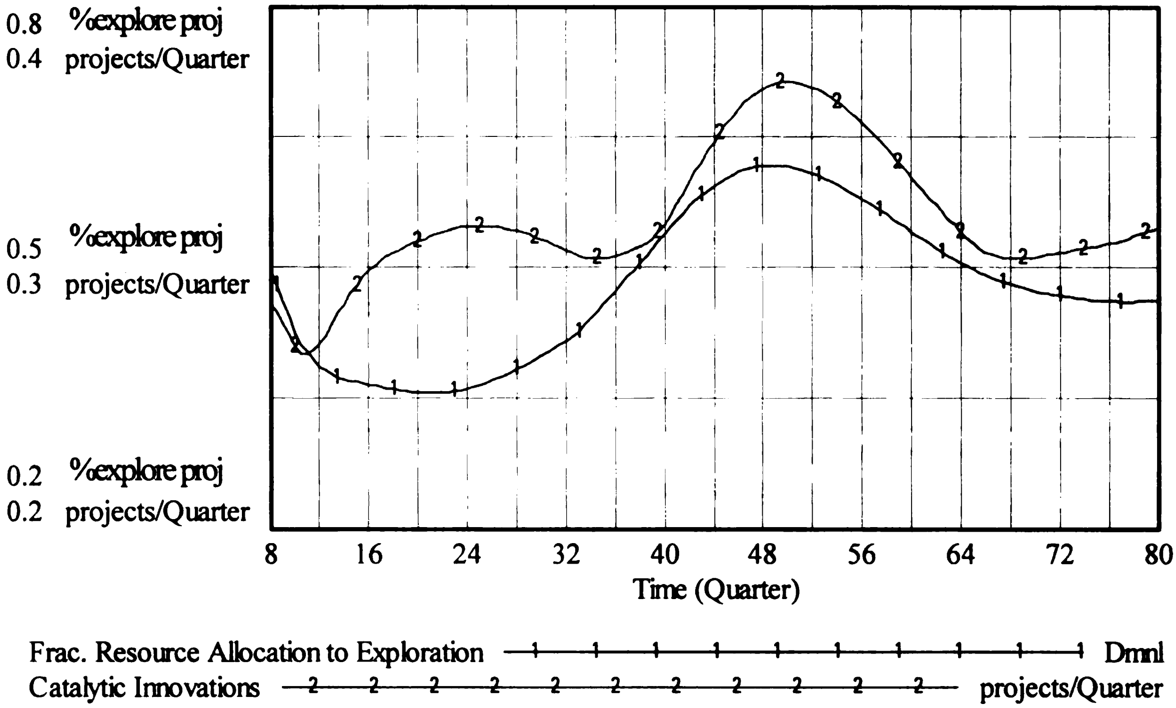


Figure 4.14 Sensitivity of Catalytic Innovations to Changes in Fraction of Resource Allocated to Exploration Activities

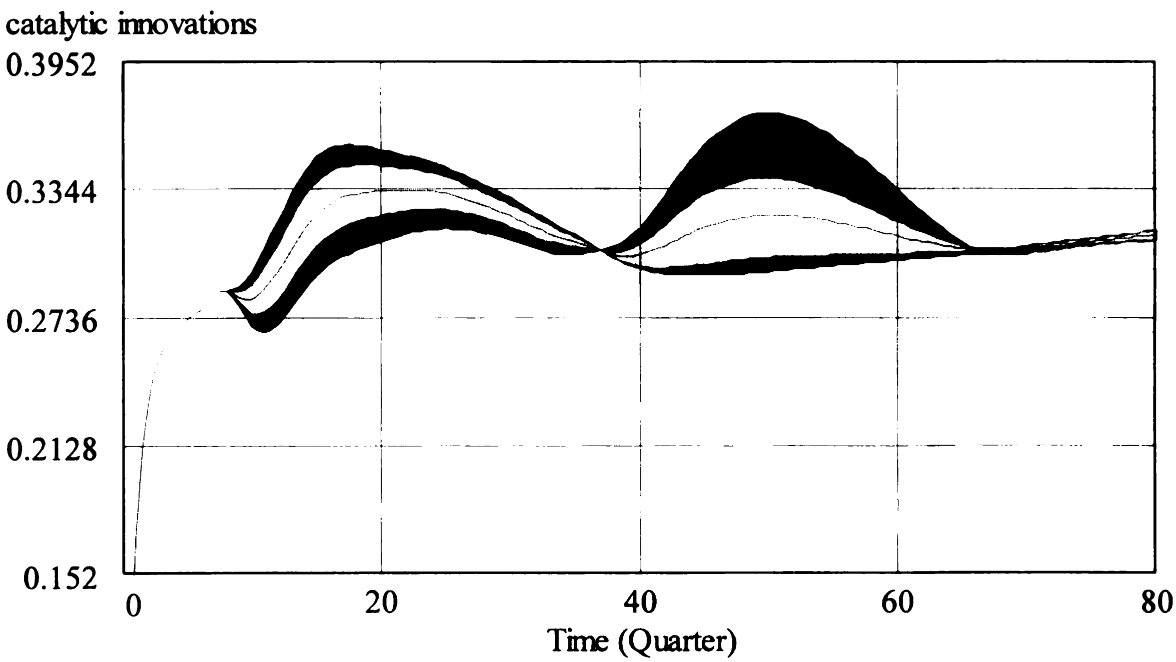


Figure 4.15 Base Case Adaptive Capacity, Technology Exploit, Marketing Proficiencies, and R&D Proficiencies

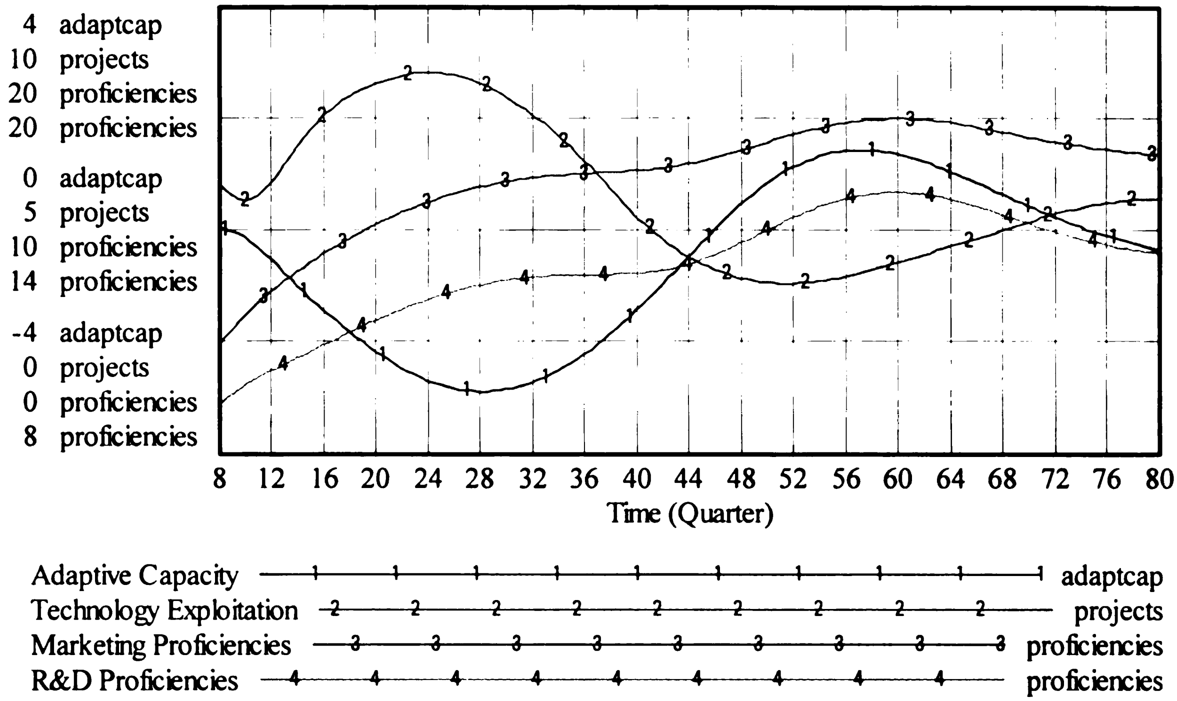


Figure 4.16 Sensitivity of Technology Exploitation to Changes in Adaptive Capacity

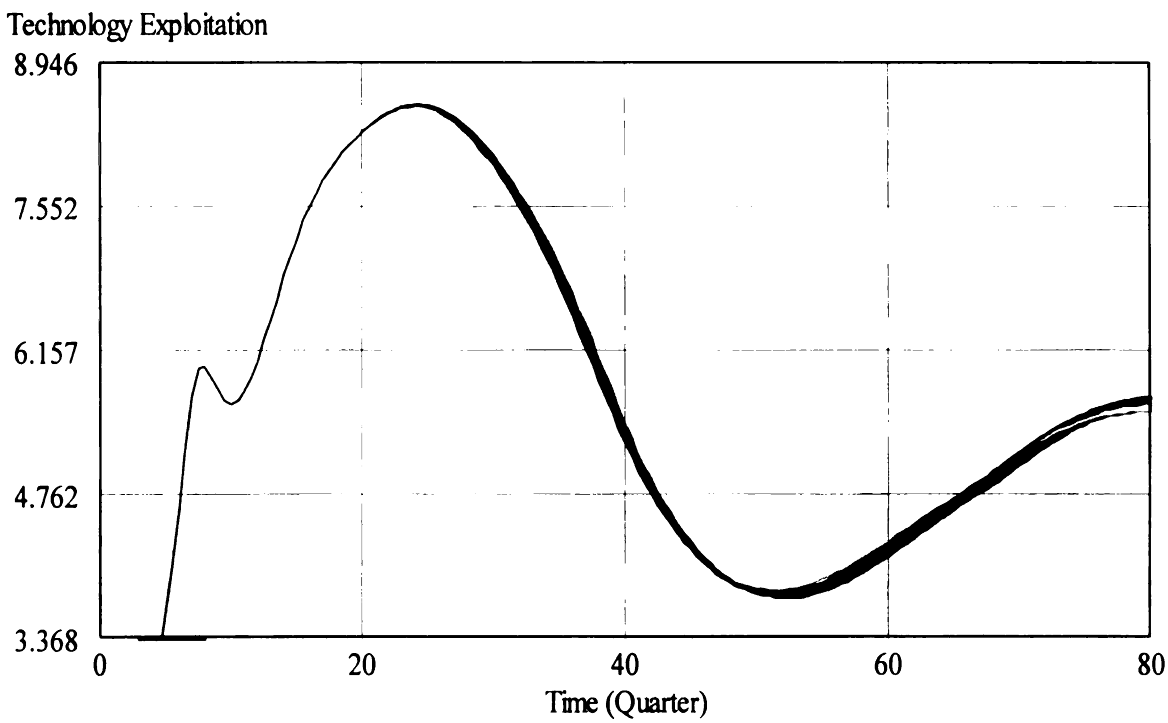


Figure 4.17 Sensitivity of Marketing Proficiencies to Changes in Adaptive Capacity

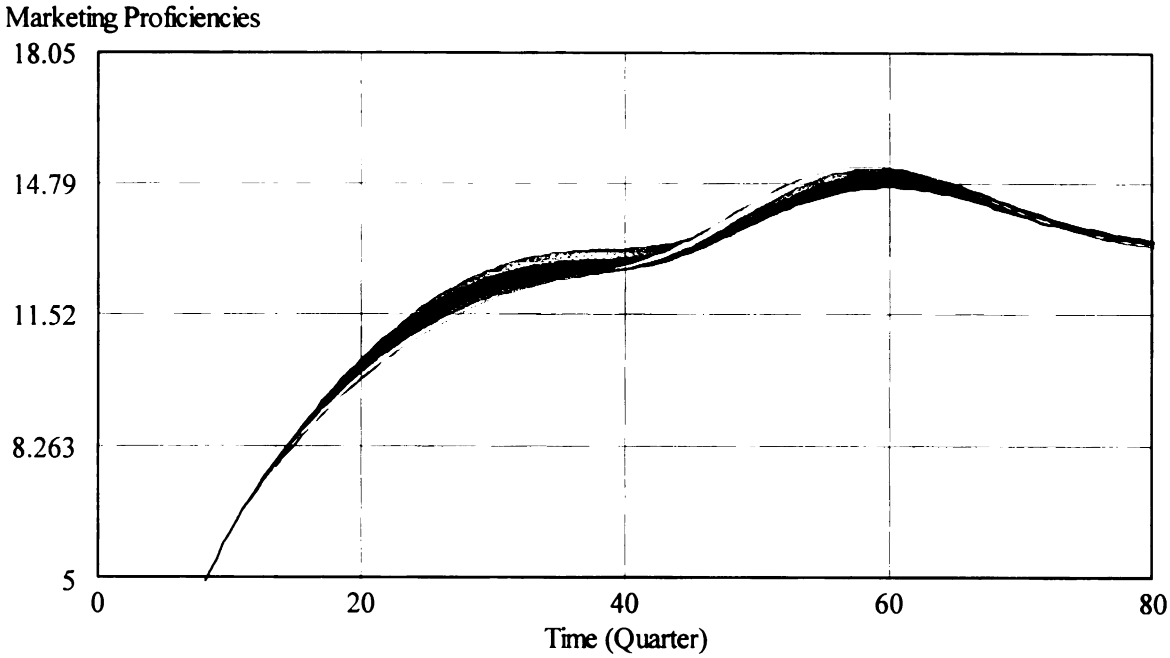


Figure 4.18 Sensitivity of R&D Proficiencies to Changes in Adaptive Capacity

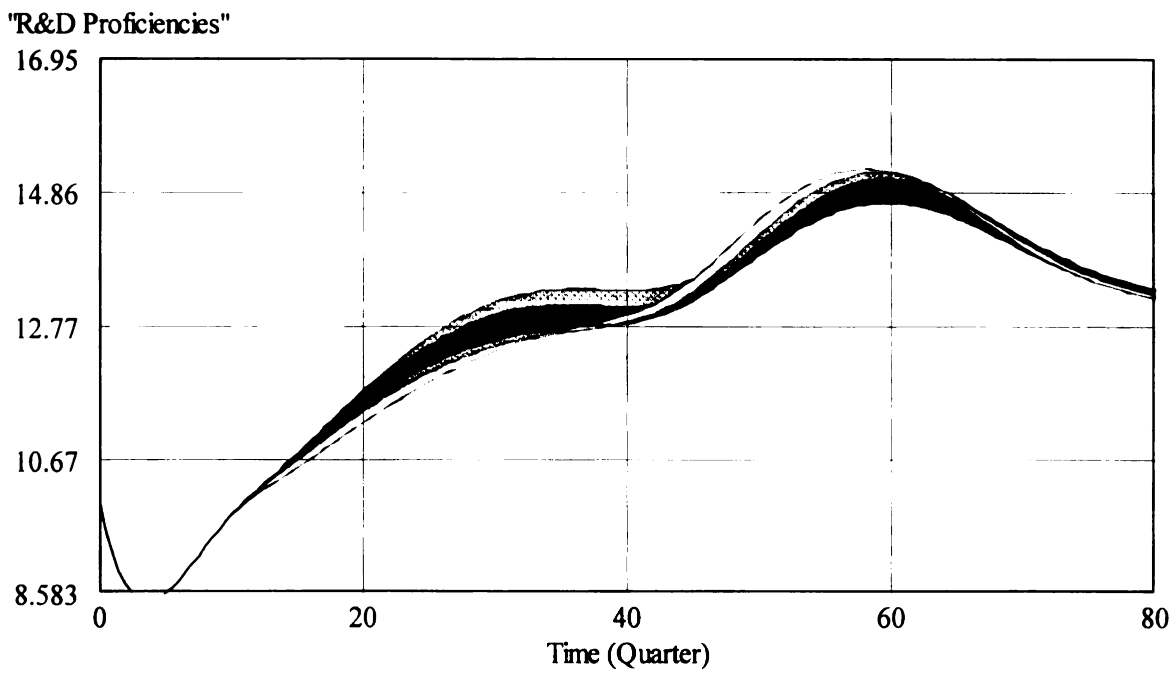


Figure 4.19 Base Case Marketing-RD Integration & Catalytic Innovations

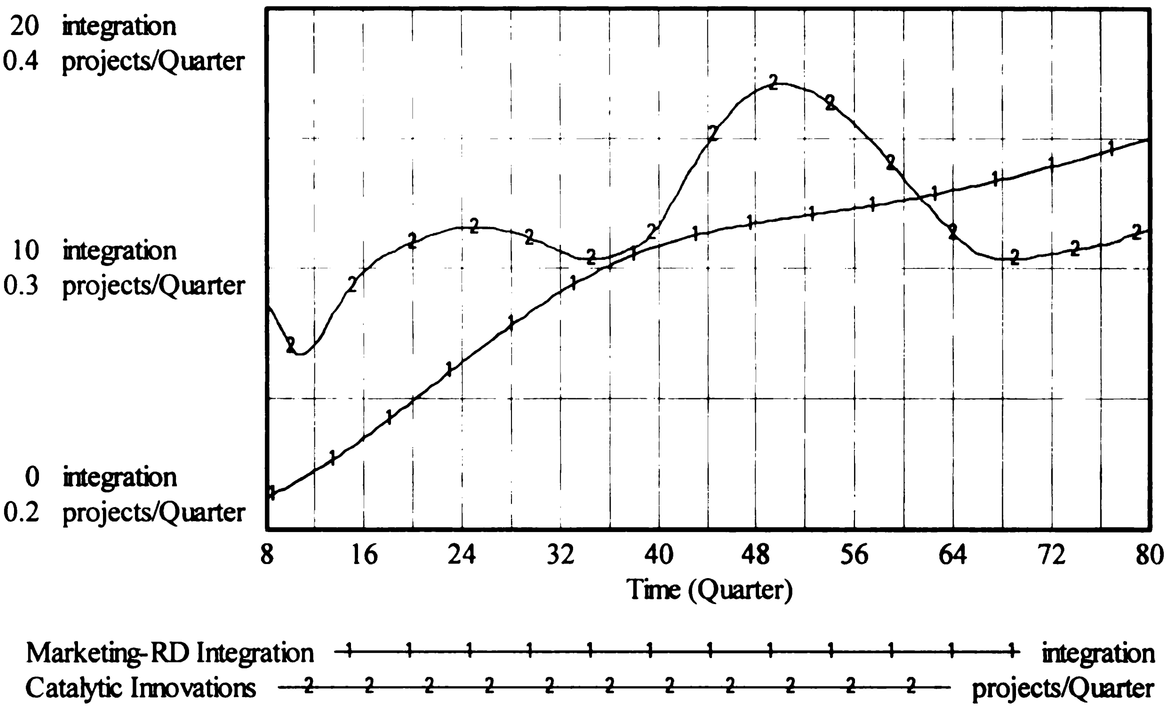
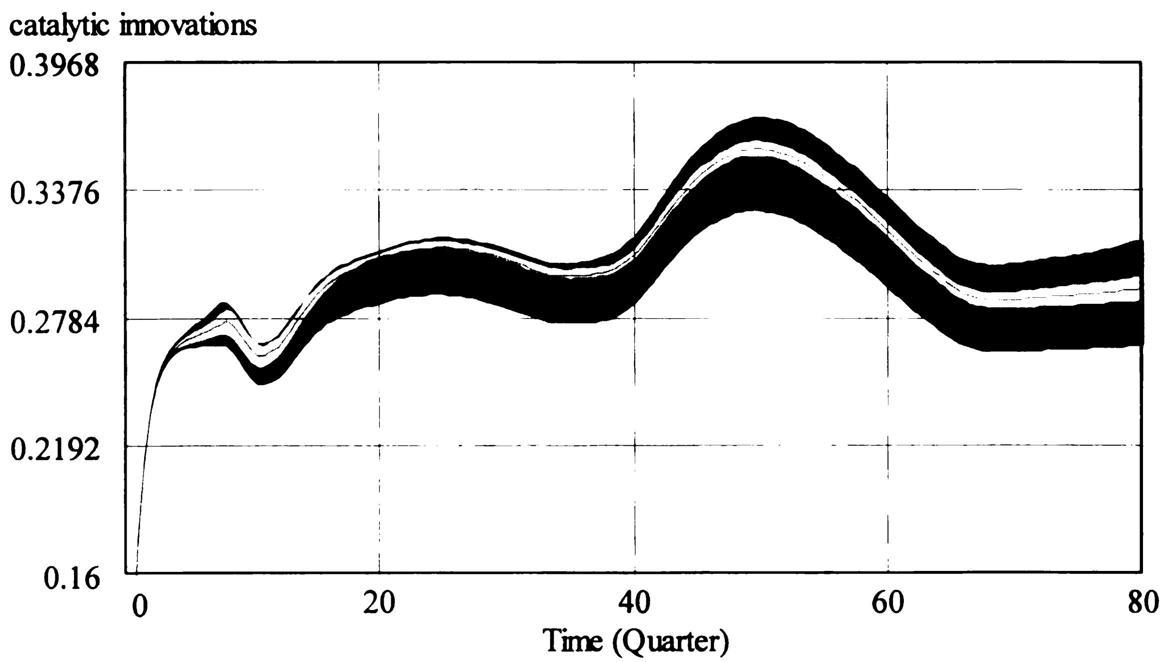


Figure 4.20 Sensitivity of Catalytic Innovations to Changes in Marketing-R&D Integration



4.8 Hypotheses

This section reports on the results from testing the hypotheses presented in Chapter 2. As the programmer sets the SD model, the relationships as described in the hypotheses are either explicitly or implicitly modeled. Thus, submitting this set of simulated data to statistical analysis may not be relevant to Study 1. For the purpose of this dissertation they are analyzed here for completeness. The values are relative, thus, coefficients from the resulting regressions are not reported.

Hypotheses H1-H11 were tested using curvilinear regression estimation techniques in SPSS 10.0.7 (SPSS, Inc., 1999). The data generated in the 32 simulations as reported in Table 4.2 were used for inputs to the curvilinear regression. Each hypothesis was first tested for the nonlinear relationship proposed in the hypotheses. The data were then submitted to an unspecified curvilinear regression whereby SPSS will fit numerous trajectories to the data and report fit statistics to the curvilinear estimation. The best fit to the data is determined by examining $R^{2,}$ the measure of the proportion of variance explained, and the F-statistic for significance. The best fitting unspecified regression is shown in Table 4.3.

Hypotheses H1-H3 consider the antecedents adaptive capacity, slack resources and R&D integration. In this simulated data, an s-shaped relationship ($\ln Y = b0 + b1 / x$) exists between a firm's adaptive capacity and the successful adoption of catalytic innovations (H1: $F = 4.95$, $R^2 = 0.009$, $p \leq 0.05$) and between a firm's slack resources and the successful adoption of catalytic innovations (H2: $F = 15.7$, $p \leq 0.001$, $R^2 = 0.063$). Although both H1 and H2 found s-shaped relationships, the R^2 values were small enough to consider the relationships inconsequential.

Table 4.3 Results of Unspecified Curvilinear Regression – Best Fitting Models

Hyp.	Type	Equation	F	p	R^2
H1	cubic	$y = b0 + b1 * x + b2 * x^2 + b3 * x^3$	13.33	.000	0.069
H2	linear	$y = b0 + b1 * x$	76.39	.000	0.253
H3	cubic	$y = b0 + b1 * x + b2 * x^2 + b3 * x^3$	5.91	.001	0.032
H4	inverse	$y = b0 + (b1 / x)$	116.15	.000	0.176
H5	quadratic	$y = b0 + b1 * x + b2 * x^2$	15.93	.000	0.056
H6	inverse	$y = b0 + (b1 / x)$	23.10	.000	0.041
H7	linear	$y = b0 + b1 * x$	3598.37	.000	0.440
H8	cubic	$y = b0 + b1 * x + b2 * x^2$	342.22	.000	0.130
H9	quadratic	$y = b0 + b1 * x + b2 * x^2 + b3 * x^3$	30.00	.000	0.019
H10	growth	$\ln y = b0 + b1 * x$	2771.09	.000	0.377
H11	linear	$y = b0 + b1 * x$	1963.38	.000	0.506
P1	inverse	$y = b0 + (b1 / x)$	58.01	.000	0.177
P2	quadratic	$y = b0 + b1 * x + b2 * x^2$	6492.05	.000	0.587
P3	inverse	$y = b0 + (b1 / x)$	235.39	.000	0.093
P4	quadratic	$y = b0 + b1 * x + b2 * x^2$	986.68	.000	0.177

The unspecified curvilinear regression for H1 found support for a linear relationship (y = b0 + b1x) between slack resources and the adoption of innovations (F = 76.39, p = 0.001, R^2 = 0.253). Hypothesis H3 (marketing/R&D integration – catalytic innovation) was not supported, as a linear relationship does not exist (F = 1.78, p = 0.183). Although the relationship can best be fit with a cubic model, the R^2 is low.

Hypotheses H4 – H6 look at the adoption of catalytic innovations as an antecedent to technological knowledge exploitation, marketing proficiencies, and R&D proficiencies. The s-shaped trajectory of H4 is supported (H4: F = 111.17, $p \leq 0.001$, R^2 = 0.170), although an inverse regression better fits the data. Even though H5 and H6 can be described by s-shaped curves, the relationships can be considered inconsequential (H5: F = 13.38, $p \leq .001$, $R^2 = 0.024$; H6: F = 14.62, $p \leq .001$, $R^2 = 0.026$).

Hypotheses H7- H9 test the s-shaped relationship between the antecedents technology knowledge exploitation, marketing proficiencies, R&D proficiencies and the dependent variable, NP program success. Only H7 is supported (H7: s-shaped relationship - F = 1372.18, p = .000, $R^2 = .231$). H8 and H9 proposed linear relationships that were found but the R^2s were low (H8: F = 10.21, $p \leq .001$, $R^2 = 0.002$; H9: F = 24.79, p = .000, $R^2 = 0.005$). Even the unspecified nonlinear relationships with higher R^2 values, as reported in Table 4.4, are inconsequential.

Hypotheses H10 and H11 test the feedback relationships from NP program success to adaptive capacity and slack resources. The s-shaped relationships are supported including the inverted s-shaped for H10 (H10: F = 1930.04, p .000, $R^2 =$ 0.297; H11: F = 1782.76, p = .000, $R^2 = 0.482$). H10 is better described by an inverse relationship ($y = b0 + b1 / x$) and a linear relationship was found to best describe H11.

As previously mentioned, five new paths were introduced to the model as shown in Figure 4.1. These paths were also tested using curvilinear regression. Paths P1 and P4 were supported as an s-shaped relationship was found to be significant (P1: F = 111.17, p = .000, $R^2 = 0.170$; P2: F = 6076.52, p = 0.000, $R^2 = 0.571$) but P3 and P4 resulted in low R^2s (P3: F = 195.92, p = .000, $R^2 = 0.041$; P4: F = 413.18, p = 0.000, $R^2 = 0.083$). Again, all of these relationships can be explained with greater precision with unspecified nonlinear equations (Table 4.4). In comparing the model in Chapter 2 with the model in Figure 4.1, P1 replaces H1, P2 replaces H4, P3 replaces H5 and P4 replaces H6. For each of the four new paths modeled, the R^2 is considerably higher than the R^2 for the path it replaced (see Table 4.4 for these comparisons). These results lend support for the improved model.

To evaluate the moderating relationship of adaptive capacity, (P5), an interaction term was generated. Multiple linear regression was conducted on each of the dependent variables, technology exploitation, marketing proficiencies, and R&D proficiencies. The interaction term (technology knowledge acquisition * adaptive capacity) was significant for all three regressions ($p = 0.000$) lending support for P5 that adaptive capacity will act as a moderator to knowledge utilization in the NP process. However, this is not conclusive, as it may actually be an artifact of how the SD model was programmed.

It must be noted that even though many of the hypotheses are not supported this does not indicate an incorrect SD model. First it must be understood that the simulated data was obtained by deliberately modeling in 'low' or no relationships between constructs. Thus, marginal effects in the model will lead to inconsequential effects in the simulated data regression analysis. Most importantly, as previously noted, in retrospect building hypotheses for simulated data is inappropriate. The question to ask is whether the model can accurately represent the phenomena of interest. Sterman (2000) contends that "no model can be verified or validated because all models are wrong. All models, mental or formal, are limited, simplified representations of the real world. They differ from reality in ways large and small, infinite in number" (pg. 846). Levine et al., (1992) and Sterman suggests ways of testing models to uncover flaws and improve models so that they closely as possible reflect the reality of the system being studied. They suggest: testing boundary assumptions, reconciling the model structure with vested parties, testing extreme conditions, checking for behavior anomalies and surprise behaviors, and conducting sensitivity analyses. All of these steps were taken to ensure that this model as accurately as possible reflects the evolving NP processes of small engineering driven firms.

4.9 Discussion and Conclusions

A fundamental question introduced in Chapter 1 is whether the adoption of innovations can be tied to the success of a firm's NP program. The case studies and resulting system dynamics simulations shows support for this link. However, it is not necessarily the innovation itself that helps to promote a healthy NP program, but more accurately, it is the knowledge gained from adopting the innovation that leads to a more successful program. Catalytic innovations also may contribute to the success of new products. Since they bring unanticipated knowledge gains, more NP projects can be undertaken by the organization.

This study supports the March (1991) proposition that a firm may hinder its performance by exclusively engaging in either exploration (research) or exploration (development). Since the adoption of innovations is a part of most technologically oriented firms' research process, too much of a focus on catalytic innovations may possibly be detrimental to NP performance. Adopting innovations requires resources in forms of man-hours and financing. If adequate resources are not available to support these activities, the financial bottom line may be affected.

The results of this study also suggest a decision-rule criterion for determining the proper balance between exploration and exploitation activities. In this model a 50/50 allocations was not seen to maximize NP program success (see Figure 4.21). In *this* *study,* NP program success is maximized with about a 25-75 split on exploration/ exploitation activities. When too many resources are allocated into expense research activities, the firm cannot take on exploitation activities that allow the creation of new products. Obviously NP profits cannot be generated until the products reach the marketplace, thus, a major focus on exploitation activities appears to be more important than emphasizing exploration activities especially when resources are limited.

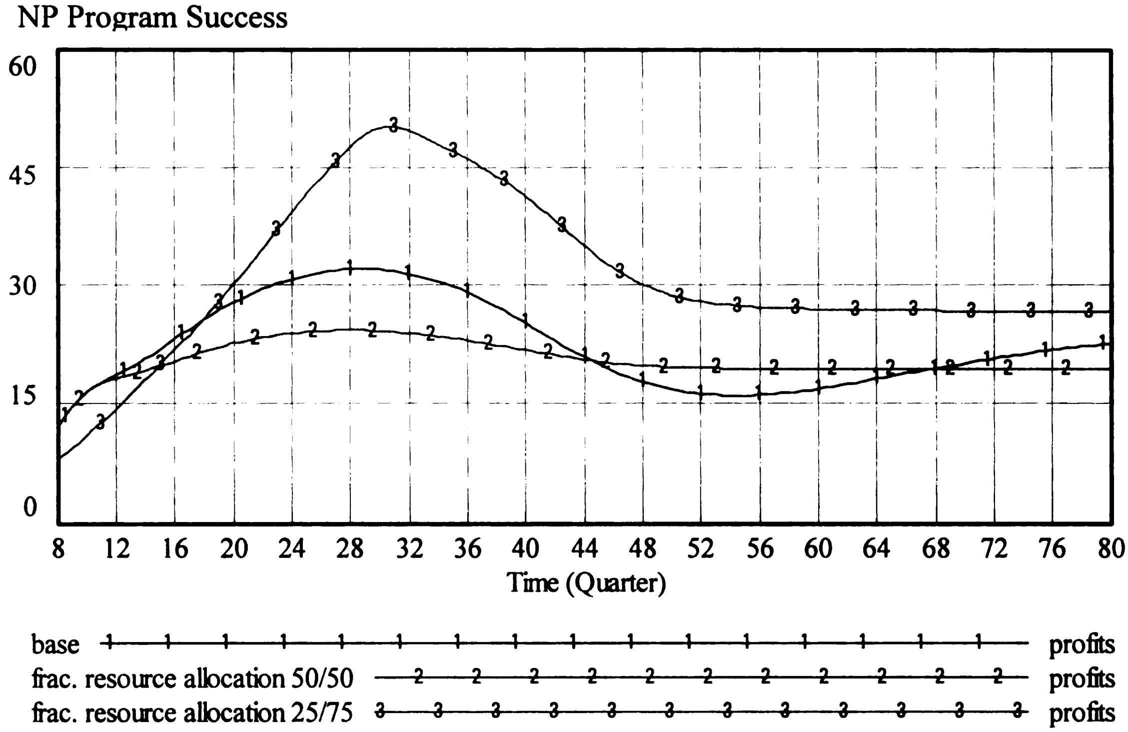
This study also supports Cyert and March's (1963) contention that slack resources are necessary (but not sufficient) for the success of the adoption of innovations. This is particularly true for catalytic innovations whose outcome may not always be successful. Exploration activities have highly variant results on the NP process; sometimes they may be wildly successful, occasionally ruinously unsuccessful, but usually moderately successful (March, 1991). Firms must be able to have sufficient resources so that unsuccessful exploration does not become a disadvantage to the firm. They must also have a propensity towards exploration.

System dynamics models provide a fundamental opportunity for studying a firm's strategic policy. One of the policies examined in this study was the lockout of new knowledge due to the lock-in to core competencies (Leonard-Barton, 1992). As proposed in Chapter 1 and 2, a firm may become ensnared in a "success trap" when performance targets are being exceeded. It may take on a 'if its not broken, don't fix it' attitude and will focus on exploiting an existing knowledge base through a focus on development. This can lead to lower performance levels as products become outdated. This study shows that a firm must balance exploration and exploitation activities so as not to end up in the success trap. Exploration activities are required for a sustained flow of new knowledge, and exploitation activities are required for continual improvement of the existing product line.

The case studies suggest that a firm may utilize its knowledge stock based on its past performance. Newer knowledge is emphasized more when competition increases or NP performance is in possible jeopardy. Older knowledge is emphasized when there is no threat to performance. This may also increase the potential for a firm to fall into the success trap. A firm may increase the success of the adoption of innovations by arranging for adequate slack resources and encouraging R&D marketing integration. The most important outcome of the adoption of innovations is that the acquisition of new knowledge that can be used to develop more competitive products for the marketplace. Adaptive capacity, or a firm's willingness to be open to new ideas, does not appear to be a requirement for the successful adoption of innovations, but instead may play a more consequential role in how knowledge is utilized once it has been obtained. Future research evaluating how a firm's changing adaptive capacity affects decision-making policies in the NP process may be worth investigating.

Although catalytic innovations are not an essential prerequisite to ensure NP success, they may substantially increase the knowledge base of the firm for building new products. A firm can foster an environment for the emergence of catalytic innovations by encouraging research projects, even though they may fail, and by supporting exploration activities with the necessary resources.

Figure 4.21 Resource Allocation Effects on NP Program Success



CHAPTER 5

RESEARCH METHOD – STUDY 2: LONGITUDINAL STUDY

5.1 Introduction

Study 2 involved conducting longitudinal panel data collection in order to test the hypotheses as outlined in Chapters 2 and 3. Measures at time 1 and their corresponding change scores at times 2 and 3 were collected in order to observe the *change* over time that occurs in the NP development process. Chapter 5 reports on the data collection, the structural equation modeling linear growth curve methodology, and the results of the data analyses.

5.2 Sampling Frame

The hypotheses were tested using longitudinal data collection over three time periods based on the sampling frame of 101 companies/divisions owned by a manufacturing conglomerate based in New Jersey, USA. This sample is a unique family of engineering and technology-based companies that manufactures a diverse line of products with a primary focus on the metals industry. The firms are also involved in other manufacturing industries such as optics, semiconductors and lighting displays. Divisions are located in Australia, Belgium, Brazil, England, France, Germany, India, Japan, Korea, Mexico, Taiwan and Turkey. In all of these companies, excellence in engineering is the key shared characteristic.[1]

The VP of Marketing of the parent company notified each of the one hundred

[1] from company web page. Consistent with non-disclosure, identity of company is not available

firms/divisions of the intended study in a letter. Each was asked to participate in the year- long study. In July 2001, survey 1 was sent to the President/General Manager, VP Engineering/CTO and the VP Marketing/Marketing Manager of the 101 firms/divisions, as these individuals are most familiar with their new product development processes. Eighty-seven surveys were returned representing seventy-three firms/divisions. Many of the surveys were completed jointly by several people in key positions in the new product process. The other 28 companies either declined to be involved in the study or responded that their primary function was sales/support, thus they were not involved in new product development and could not answer the survey. Of the 73 firms responding, 55 firms provided information regarding innovations they had adopted into their organization within the last thirty-six months. As the study centered on the adoption of innovations, only those firms providing this information were administered survey 2.

Forty-three firms responded to survey 2, which was sent in early December, 2001. One company had ceased operation, one had merged with another sister company, one company had a change in President and the new President did not feel qualified to respond, and one respondent had suddenly died since the first survey. The other eight firms were considered nonrespondents. In April 2002, survey 3 was delivered to the 53 firms that had originally responded to survey 1 with information regarding adopted innovations. Only the two firms that were no longer in existence were excluded from the original 55 respondents. Forty-two firms responded to survey 3. The final count was 38 firms responding to surveys 1, 2,and 3, six firms responding to surveys 1 and 3, and four firms responding to surveys 1 and 2. This resulted in a total sample size of 49 firms or a

48.5% response rate for the entire study. Missing data was imputed for ten firms not responding at times 2 or 3. This method will be explained in the next section.

5.3 Missing Data Imputation

Missing data is a classic problem in longitudinal studies. Missing data may occur due to several different reasons; non-response by subjects unable or unwilling to respond to the study, missing occasions when a subject participates in the study during a number of occasions but not all times, item non-response, and/or failure to obtain measurements at equal time periods. In addition to the reasons why data may be missing, the mechanism by which missing data are generated is also important. Little and Rubin (1987) describe three different mechanisms. Data that are *missing completely at random* (MCAR) does not depend on its value or the value of any other variables. Data that is *missing at random* (MAR) may depend on the value of any of the manifest variables but is unrelated to the scores on any of the latent variables. Data that are *non-ignorable missing* is related not only to the values of the manifest variables but also to the latent variables (Bijleveld, et. al, 1998). When data is assumed to be MCAR, a common approach is to run computations using listwise (LD) or pairwise (PD) deletion and to generalize the results to the population from which the sample was drawn. This leads to consistent although not necessarily efficient estimates. If the data is MAR, LD and PD estimates may also yield biased results. Another method of addressing the missing data problem is to replace each missing value with the observed mean of the variable. Mean imputation (MI) can lead to biased variance and covariance estimates.

An alternative solution to missing data is based on full-information maximum likelihood (Arbuckle, 1996). This imputation method uses all the information of the observed data including estimates of the population means, variances and covariances. Matrices of the estimates of the means and covariances are obtained from confirmatory factor analysis. These matrices are used to generate the missing data for an individual case using the following formula:

$$\overline{E(x_u | x_m)} = \hat{\mu}_u + \hat{\Sigma}_{um} \hat{\Sigma}_{mm}^{-1} (x_m - \hat{\mu}_m) \tag{5.1}$$

where

- x_u is the vector of unknown measurements which are being calculated,
- x_m is a vector containing the measurements that are observed for the case,
- $\hat{\mu}_m$ and $\hat{\mu}_u$ are estimates of the elements of population mean, μ^*, corresponding to the measured and unmeasured values, respectively.
- $\hat{\Sigma}_{mm}$ contains the row and columns of the population covariance matrix, Σ^*, corresponding to the measured covariance values, and
- $\hat{\Sigma}_{um}$ is a submatrix obtained from Σ^* by deleting the rows corresponding to the measured values and deleting the columns corresponding to the unmeasured values.

An example will help to illustrate this technique. Marketing proficiencies were measured by four variables at time 1 and the same four variables at time 2. Thus, the following matrices were estimated for the mean and covariances based on the available data from all respondents at time 1 and time 2.

$$\hat{\mu}^* = \begin{bmatrix} 3.23 \\ 4.33 \\ 3.86 \\ 3.70 \\ 3.70 \\ 4.74 \\ 5.19 \\ 4.30 \end{bmatrix} \text{ and } \hat{\Sigma}^* = \left[\begin{array}{cccc|cccc} 1.71 & 1.02 & 0.93 & 1.08 & 1.93 & 1.30 & 1.19 & 1.24 \\ 1.02 & 2.27 & 1.74 & 1.33 & 1.20 & 2.51 & 1.75 & 1.40 \\ 0.93 & 1.74 & 2.60 & 1.43 & 0.84 & 1.83 & 2.30 & 1.57 \\ 1.08 & 1.33 & 1.43 & 2.12 & 1.05 & 1.42 & 1.57 & 2.42 \\ \hline 1.93 & 1.20 & 0.84 & 1.05 & 3.26 & 2.06 & 1.49 & 1.67 \\ 1.30 & 2.51 & 1.83 & 1.42 & 2.06 & 3.53 & 2.26 & 1.82 \\ 1.19 & 1.75 & 2.30 & 1.57 & 1.49 & 2.26 & 3.11 & 2.23 \\ 1.24 & 1.40 & 1.57 & 2.42 & 1.67 & 1.82 & 2.23 & 3.65 \end{array}\right]$$

In this study, case #1 had missing data for survey 2, however, data for all variables were available for survey 1. Thus, for this individual,

$$\hat{\mu}_m = \begin{bmatrix} 3.23 \\ 4.33 \\ 3.86 \\ 3.70 \end{bmatrix}; \hat{\mu}_u = \begin{bmatrix} 3.70 \\ 4.74 \\ 5.19 \\ 4.30 \end{bmatrix}; \hat{\Sigma}_{mm} = \begin{bmatrix} 1.71 & 1.02 & 0.93 & 1.08 \\ 1.02 & 2.27 & 1.74 & 1.33 \\ 0.93 & 1.74 & 2.60 & 1.43 \\ 1.08 & 1.33 & 1.43 & 2.12 \end{bmatrix};$$

$$\hat{\Sigma}_{um} = \begin{bmatrix} 1.93 & 1.20 & 0.84 & 1.05 \\ 1.30 & 2.51 & 1.83 & 1.42 \\ 1.19 & 1.75 & 2.30 & 1.57 \\ 1.24 & 1.40 & 1.57 & 2.42 \end{bmatrix}; \text{ and } \hat{x}_m = \begin{bmatrix} 2 \\ 6 \\ 6 \\ 5 \end{bmatrix} \text{ so that } \overline{E(x_u | x_m)} = \begin{bmatrix} 2.261 \\ 6.358 \\ 6.095 \\ 5.447 \end{bmatrix}$$

In this manner missing data was imputed for case #1's marketing proficiencies data at time 2 in order to have a complete data set. As previously noted, six cases had missing data for survey 2 and four had missing data for survey 3. This imputation method was used to calculate estimates of the missing variables for these cases. Overall, this results in 10.20% of imputed data in this study.

5.4 Measurements

Two rounds of questionnaire pre-testing were conducted using measures either adapted or developed from the literature. In the first round, five managers each with more than ten years experience in NPD commented on the survey and the cover letter. Their comments and suggestions resulted in revisions before conducting pretests in two companies.

In survey 1, seven point Likert scales (1 = strongly disagree to 7 = strongly agree) were used throughout, except for the performance scales (which were –3 to +3, as specified below). In surveys 2 and 3 in order to collect change scores data, seven point Likert scales (-3 = significantly decreased to +3 = significantly increased) were used when repeated measures data were collected.

In the final analyses some questionnaire items were not used in surveys 2 and 3 because: (1) exploratory factor analysis (EFA) revealed more than one factor and only the first was chosen; (2) tests for measurement invariance over time revealed inconsistencies in a measure, or (3) subsequent confirmatory factor analysis (CFA) suggested that the measure be dropped. The final measures used in the model analyses are presented in Appendix C. The following list of constructs and associated items were used in the final analysis of the longitudinal study:

Adaptive Capacity (t=1, Cronbach's alpha (α) = 0.809; t=2, α = 0.745; t=3, α = 0.817). One of the goals of this study was to operationalize the concept 'adaptive capacity', which this study had previously defined as a firm's willingness, flexibility and ability to adapt to its environment. Adaptive capacity was based on concepts of absorptive capacity (Cohen and Levinthal, 1990), flexibility and marketing/R&D orientation from management and marketing literature. In order to separate the specifics of a marketing absorptive capacity from an R&D/technical absorptive capacity, five constructs were included in survey 1: market orientation (5 items based on Jaworski and

Kohli, 1993), R&D/technology orientation (5 items based on Jaworski and Kohli), strategic flexibility (5 items - 3 based on Jaworski and Kohli and 2 new), technical absorptive capacity, and marketing absorptive capacity (4 items each, all new based on Cohen and Levinthal, 1990). After tests of construct validity, described in the next section, only three of the items measuring strategic flexibility were used in surveys 2 and 3. The two items based on Jaworski & Kohli's 1993 study on market orientation. and one new measure, which emphasized the firm's ability to adapt to changes in its environment, were used in the final analyses.

Slack Resources ($t=1$, $\alpha = 0.809$; $t=2$, $\alpha = 0.741$; $t=3$, $\alpha = 0.852$). Slack resources are those resources not previously committed to other organizational departments or programs. It was measured by four items based on Calantone, et al., (forthcoming). These were used to measure the abundance of capital equipment, material supplies, R&D resources and advertising resources available for new product development.

Marketing-R&D Integration ($t=1$, $\alpha = 0.899$; $t=2$, $\alpha = 0.894$; $t=3, \alpha = 0.913$). Four items based on Li and Calantone (1998) were used to measure the degree to which marketing concepts were considered in engineering/R&D decisions. During the survey pre-test it was found that most of the firms in this study only had an informal marketing departments, and therefore, the marketing department was not involved in the engineering process. However, when further pressed, respondents confirmed that it was a matter of standard policy to consider customers' needs, pricing issues, competitive positions and market conditions when building new products. Thus, the four questions used in this study reflect this implicit use of marketing issues in the NP process. This is an important distinction that should be recognized in future uses of measuring this construct.

Successful Adoption of Innovations (t=1, $\alpha = 0.713$; t=2, $\alpha = 0.823$; t=3, $\alpha = 0.875$). Both Tornatzky and Klein (1982) and Robertson and Gatignon (1986) argue that a measure of success for the adoption of innovations should be the implementation of the innovation within the firm. Eight measures were developed for this study that focused on the use of innovations within an organization after adoption. As this study's unit of analysis was the *NPD program*, each respondent was first asked to list three innovations that the firm had adopted in the last thirty-six months. These three innovations were tracked throughout the remainder of the study.

Secondly, the eight measures developed for this study were then asked with regards to the innovations identified in the first section. The average of the responses across the three innovations was used as the final score for each measurement. Surveys 2 and 3 followed a similar format, but listed with each question the innovations identified by the respondents in Survey 1 for ease of recall.

For a list of innovations cited by these firms see Appendix C. After exploratory factor analysis and evaluations of construct validity, only five of the original eight measures were used in surveys 2 and 3. The final analysis used three of these items. The final list of measures used in also in Appendix C.

Knowledge Exploitation (t=1, $\alpha = 0.843$; t=2, $\alpha = 0.827$; t=3, $\alpha = 0.805$). Knowledge exploitation was measured by five items based on March's 1991 concept of technology exploration/exploitation. These items did not hold up against tests of construct validity and reliability. Thus, these measurements were eliminated from

Surveys 2 and 3 and four new measures were created for the subsequent studies. After the CFA, one item was dropped resulting in three items in the final analyses.

The four new questions were asked twice in survey 2; once to get an initial measure and the second time to determine their relationship to the innovations identified in survey 1. The first set of questions was in part 1 of survey 2 and the second set of questions was in part 2 of survey 2, which focused on the outcomes to the adoption of innovations. Although not preferred, measuring both the initial condition and the effects of the adoption of innovations on knowledge exploitation at time 2 was a way of correcting the unusable items in survey 1. The wording of the questions and their location within survey 2 helped to guide the respondent to answer these questions from the two different time frames.

Surveys 2 and 3 framed the questions with respect to the three innovations identified in survey 1 so that each question was asked up to three times, once for each innovations reported in survey 1. The responses were averaged across the three innovations and were used as measures of program-level effects. See Figure C.1 in Appendix C for an example of the question presentation.

Marketing Proficiencies (t=1, $\alpha = 0.803$; t=2, $\alpha = 0.808$; t=3, $\alpha = 0.781$). Eight items were originally used to measure marketing proficiencies in survey 1. Five of the items were borrowed from Song and Parry (1997). Three additional items were added based upon the interests of the parent company sponsoring the longitudinal study. As these last three items were directly related to the marketing scope of the company, it was not surprising that these three items had the best construct reliability and were retained for the remainder of the study. The marketing proficiency measures in survey 2 and 3 were framed with respect to the innovations being tracked. These measures were averaged across the three responses pertaining to the three innovations in the same manner as previously described for the 'knowledge exploitation' scale.

R&D Proficiencies (t=1, $\alpha = 0.889$; t=2, $\alpha = 0.805$; t=3, $\alpha = 0.839$). Four measures for R&D proficiencies were borrowed from Song and Parry. A fifth was added for this study but was deleted after survey 1. The four remaining items were used to measure a firm's ability to conduct engineering/R&D activities *after* adopting an innovation. These four items were asked for each of the three adopted innovations and averaged for a program level measure as previously described for the 'knowledge exploitation' scale.

New Product Program Success (t=1, $\alpha = 0.912$; t=2, $\alpha = 0.912$; t=3, $\alpha = 0.938$). In survey 1, fifteen measures were used to evaluate the success of the new product program. Six measures were borrowed from Calantone, et al. (forthcoming), which were originally based on Griffin and Page (1996). Two additional items were based on Griffin and Page (1996). The first eight measures were indicators of NPD program success for profits and sales relative to competitors and firm objectives. These eight measures used semantic scales anchored –3 (a great failure) to +3 (a great success). Three of these eight measures were eliminated because an EFA indicated two orthogonal constructs. The remaining five items were repeated in surveys 2 and 3 although only four were used in the final analysis based on the construct validity results.

The remaining seven questions pertaining to new product performance were only administered in survey 1. These questions were primarily used in developing the system dynamics model in Study 1 and were thus not repeated in surveys 2 and 3.

5.4.1 Measurement Means

Table 5.1 shows the means, standard deviations, and confidence intervals of the constructs at each time point. The means were calculated by averaging across the items used to measure each construct. The standard errors and confidence intervals are also reported.

The Durbin-Watson test for first-order serial correlation was also conducted. The d statistic, defined as

$$d = \frac{\sum_{t=2}^{t=n} (\hat{u}_t - \hat{u}_{t-1})^2}{\sum_{t=1}^{t=n} \hat{u}_t^2}$$

is the ratio of the sum of squared differences in successive residuals to the calculated sum of square residuals (Gujarati, 1995). The residuals, $\hat{u}_t$, are calculated from the first-order regression analysis in SPSS. The DW test sets boundary limits for the range of d to determine the existence of positive or negative autocorrelation. The lower bound, d_L, and the upper bound, d_U, are determined from tables established by Durbin and Watson. For this study d_L is set at 1.503 and d_U is set at 1.585. If d falls within the range of $d_U < d < 4-d_U$, no autocorrelations exists. If d falls within the range of $0 < d < 1.503$, positive autocorrelation exists and if d falls within the range of $4- d_L < d < 4$, negative autocorrelation exists. From Table 5.1 it can be seen that only the construct, 'successful adoption of innovations', was positively autocorrelated on time periods 1 and 2.

Table 5.1: Means of Constructs at Each Time Period

	Adaptive Capacity	Slack Resources	Marketing-R&D Integration	Successful Adoption of Innovations	Knowledge Exploitation	Marketing Proficiencies	R&D Proficiencies	NP Program Success
mean t=1	5.20	3.55	5.25	5.83	4.62	4.07	4.93	0.91
(std dev) [1]	(1.21)	(1.52)	(1.16)	(0.788)	(1.15)	(1.21)	(1.26)	(1.15)
Confidence Interval	(2.82,7.57)	(0.57, 6.53)	(2.98, 7.52)	(4.29, 7.37)	(2.37,6.87)	(1.70, 6.44)	(2.46, 7.4)	(-1.34, 3.16)
mean t=2	5.87	3.32	5.73	6.92	5.54	4.53	5.78	1.55
(std dev) [2]	(1.25)	(1.52)	(1.42)	(1.58)	(1.35)	(1.50)	(1.30)	(1.63)
Confidence Interval	(3.42, 8.32)	(0.34, 6.30)	(2.95, 8.51)	(3.82, 10.0)	(2.89, 8.19)	(1.59, 7.47)	(3.23, 8.33)	(-1.64, 4.75)
mean t=3	6.37	2.94	6.33	7.76	6.27	5.05	6.51	2.10
(std dev) [3]	(1.74)	(1.98)	(1.73)	(2.11)	(1.78)	(1.69)	(1.55)	(2.26)
Confidence Interval	(2.96,9.78)	(-0.94,6.82)	(2.94, 9.72)	(3.62, 11.9)	(2.78, 9.76)	(1.74, 8.36)	(3.47, 9.55)	(-2.32, 6.5)
d-statistic,[4] d_{12}	1.710	1.962	2.054	1.423*	1.845	2.225	1.924	1.631
d-statistic, d_{23}	1.844	1.778	1.894	2.095	2.279	2.066	2.243	1.663

1. at t=1scale 1-7 except for NP Program Success, scale of [–3, 3]
2. at t=2 change scores –3 – +3; t=2 range of possible mean values [–2, 10] except NP Program Success, range of possible values [-6,6]
3. at t=3 change scores –3 – +3; t=3 range of possible values [-5, 13] except NP Program Success, range of possible values [-9,9]
4. Durbin-Watson d-statistic tests for first order serial correlation, d12 represents times 1 and 2, d23 represents times 2 and 3, *indicates significant at $p<0.05$

5.4.2 Measurement Invariance, Reliability and Validity

Measurement invariance is the first step in construct validity for longitudinal studies. It is important for future analyses that the items measure the same concepts across time. In order to test measurement invariance, 3-group SEM models were conducted for each of the eight constructs. In the multi-group SEM the factor loadings, Λ, and the measurement errors, Θ_{ϵ}, are constrained to be equal across all three time periods. Measures that were not consistent over time were eliminated from the model. In all models, the factor loadings were found to be invariant. Only the measurement error for one item of 'successful adoption of innovation' was variant for time1 and time3. This constraint was released. As CFI is sensitive to sample size (Hu and Bentler, 1995), one of the CFI was found to be 1.0. A larger sample size is required to obtain a better estimate of this fit index. Although bootstrapping is an occasionally used to 'correct' for small samples, it is not an option in multi-group analysis. The results of the multi-group analyses are presented in Table 5.2.

Confirmatory factor analysis (CFA) was used to verify the validity and unidimensionality of the measures (Anderson and Gerbing, 1988; Bollen, 1989). CFAs were conducted for each timeframe. However, due to the small sample size running all the constructs together did not allow sufficient power to make conclusive analyses on the measurement model. Thus, for each time frame two CFAs were run; the first with the construct 'successful adoption of innovations' and its three antecedents, and the second with the construct 'NP program performance' and its three antecedents. Since this study will use bivariate linear growth curves to evaluate the hypotheses, this method is sufficient to determine reliability and validity of the constructs that will be modeled together. Table 5.3 show the measurement models fit well with the lowest comparative fit index (CFI) of 0.905, NNFI = 0.877 and the highest RMSEA = 0.103. All standardized coefficients not demonstrating convergent validity with loading less than 0.5 were eliminated. This resulted in three measures for 'adaptive capacity' and three measures for 'adoption of innovations' compared to the four invariant measures found for each in the multi-group analysis. All other constructs did not change from the multi-group analysis. The next step was to assess construct reliability and validity following Anderson and Gerbing (1988). Cronbach's alphas, reported above and in Tables 5.4, 5.5 and 5.6, ranged from 0.713 to 0.938, thus, overall the alphas were satisfactory (Nunnally 1978).

To test discriminant validity, the procedure in Anderson and Gerbing (1988) was adopted to determine whether the correlation estimate's confidence interval included 1.0. Each construct passed this test: Tables 5.4, 5.5 and 5.6 report these correlations and standard errors. The final measures used are shown in Appendix C.

5.5 Methodology

The primary focus of Study 2 was to evaluate how a dynamic variable that is changing with respect to time may affect another dynamic variable. Linear growth curves have been recently introduced into the social sciences as a means of investigating the analysis of change over time and a variable's relation to select predictors, which themselves may be changing over time (Curran, 2000; Meredith and Tisak, 1990;Willet and Sayer, 1994). Linear growth curve models (LGC or LGM) are often equated to hierarchical level models as they allow the modeling of intraindividual and

Table 5.2: Results of 3-Group Structural Equation Model to Test Measurement Invariance

	Adaptive Capacity	Slack Resources	Marketing-R&D Integration	Successful Adoption of Innovations	Knowledge Exploitation	Marketing Proficiencies	R&D Proficiencies	NP Program Success
CFI	0.954	0.940	0.942	0.913	1.00	0.938	0.906	0.983
NNFI	0.959	0.946	0.948	0.918	1.00	0.944	0.916	0.985
RSMEA	.057	0.066	0.089	0.086	0.000	0.082	0.090	0.054
90% CI	(0.000, 0.097)	(0.011, 0.103)	(0.050, 0.124)	(0.046, 0.122)	(0.000, 0.079)	(0.021, 0.133)	(0.052, 0.125)	(0.000, 0.094)
Chi - square	$\chi^2_{20} = 29$	$\chi^2_{20} = 32$	$\chi^2_{20} = 42$	$\chi^2_{19} = 39$	$\chi^2_{10} = 8.5$	$\chi^2_{10} = 19$	$\chi^2_{20} = 43$	$\chi^2_{20} = 28$
# of items	4	4	4	4	3	3	4	4

Table 5.3: Results of CFA for Each Time Period

	Time1 CFA1	Time1 CFA2	Time2 CFA1	Time2 CFA2	Time3 CFA1	Time3 CFA2
CFI	0.905	0.917	0.904	0.928	0.911	0.955
NNFI	0.879	0.894	0.877	0.907	0.886	0.943
RSMEA	0.098	0.096	0.092	0.087	0.103	0.077
90% CI	(0.048, 0.133)	(0.045, 0.131)	(0.039,0.129)	(0.029, 0.125)	(0.056, 0.137)	(0.000, 0.116)
Chi - square	$\chi^2_{71} = 101.9$	$\chi^2_{71} = 100.7$	$\chi^2_{71} = 98.52$	$\chi^2_{71} = 95.42$	$\chi^2_{71} = 105.3$	$\chi^2_{71} = 89.6$

Table 5.4: Time1 Reliabilities & Discriminant Validity Measurements

Construct	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Adaptive Capacity	**0.809**							
(2) Slack Resources	-0.490 (0.133)	**0.809**						
(3) Marketing-R&D Integration	0.681 (0.098)	-0.385 (0.136)	**0.899**					
(4) Successful Adoption of Innovations	0.320 (0.163)	-0.428 (0.147)	0.209 (0.161)	**0.713**				
(5) Knowledge Exploitation					**0.843**			
(6) Marketing Proficiencies					0.109 (0.166)	**0.803**		
(7) R&D Proficiencies					-0.233 (0.158)	0.185 (0.156)	**0.889**	
(8) NP Program Success					-0.242 (0.153)	0.329 (0.142)	0.186 (0.150)	**0.912**

Cronbach's alpha reported along the diagonal. Correlations (standard errors) on lower matrix

Table 5.5: Time2 Reliabilities & Discriminant Validity Measurements

Construct	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Adaptive Capacity	**0.745**							
(2) Slack Resources	-0.189 (0.176)	**0.741**						
(3) Marketing-R&D Integration	0.660 (0.109)	0.197 (0.160)	**0.894**					
(4) Successful Adoption of Innovations	0.174 (0.162)	-0.220 (0.158)	0.128 (0.149)	**0.823**				
(5) Knowledge Exploitation					**0.827**			
(6) Marketing Proficiencies					0.087 (0.171)	**0.808**		
(7) R&D Proficiencies					-0.080 (0.175)	-0.059 (0.172)	**0.805**	
(8) NP Program Success					-0.089 (0.162)	0.288 (0.148)	0.235 (0.155)	**0.912**

Cronbach's alpha reported along the diagonal. Correlations (standard errors) on lower matrix

Table 5.6: Time3 Reliabilities & Discriminant Validity Measurements

Construct	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Adaptive Capacity	**0.817**							
(2) Slack Resources	0.353 (0.149)	**0.852**						
(3) Marketing-R&D Integration	0.608 (0.109)	0.226 (0.154)	**0.913**					
(4) Successful Adoption of Innovations	0.200 (0.160)	0.073 (0.164)	0.251 (0.151)	**0.875**				
(5) Knowledge Exploitation					**0.805**			
(6) Marketing Proficiencies					0.094 (0.161)	**0.781**		
(7) R&D Proficiencies					0.083 (0.163)	-0.012 (0.164)	**0.839**	
(8) NP Program Success					-0.074 (.0155)	0.296 (0.144)	0.433 (0.131)	**0.938**

Cronbach's alpha reported along the diagonal. Correlations (standard errors) on lower matrix

interindividual differences over time. LGCs permit the evaluation of the general shape of individual growth trajectories and of the estimates of individual growth parameters with respect to time (Level 1 within-person analysis). All members of a population are assumed to have trajectories of the same functional form but different members may have different values of the individual growth parameters. LGCs also provides estimates for the means, variances and covariances of the individual growth parameters across all members of a population (Level 2 between-person analysis). It is at Level 2 that predictors of change are modeled to estimate the effect on interindividual growth parameters.

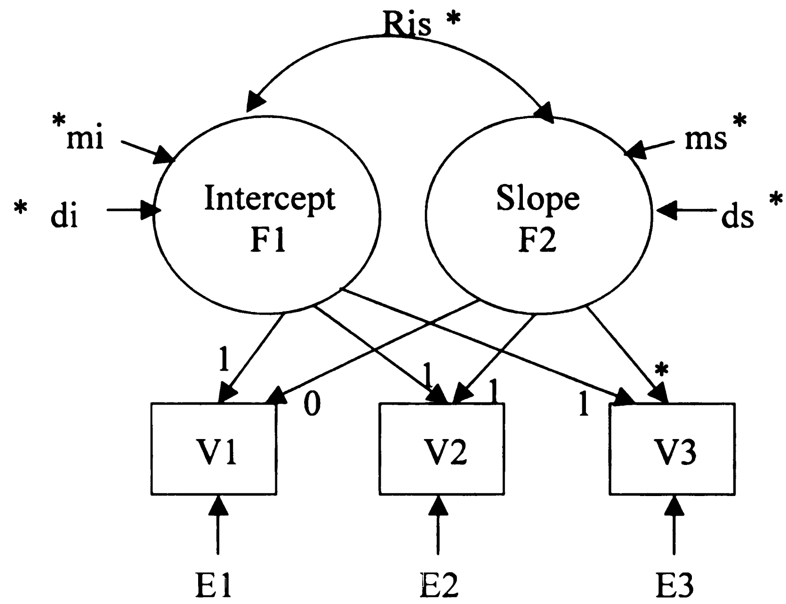
Linear growth curves were used to evaluate the hypotheses as proposed in Chapter 2. LGCs require repeated measures in balanced data panels. In order to obtain repeated measure data, the change scores collected from survey 2 were added to the initial scores obtained from the data collection at time 1 for reporting time 2 measures. Similarly, the change scores collected in survey 3 were added to the time 2 scores to obtain time 3 measures. Evaluation of the linear growth curves occurred in three stages. The first stage, measurement invariance, has been previously described. After validating measurement invariance across time, the second step is to conduct univariate linear growth models, and the final step is to evaluate the bivariate linear growth curves. This section will describe these last two steps.

5.5.1 Univariate Linear Growth Curves

Linear growth curves use information about the covariance and mean structure of repeated observed measures to define one or more underlying latent growth factors (Meredith and Tisak, 1990, Stoolmiller, 1995). Conceptually, it considers the observed measures taken over time to be indicators of an unobserved true growth trajectory. The fixed and random components of the growth trajectory are estimated via the means and variances of the latent growth factors. These types of models are shown in Figures 5.1 and 5.2.

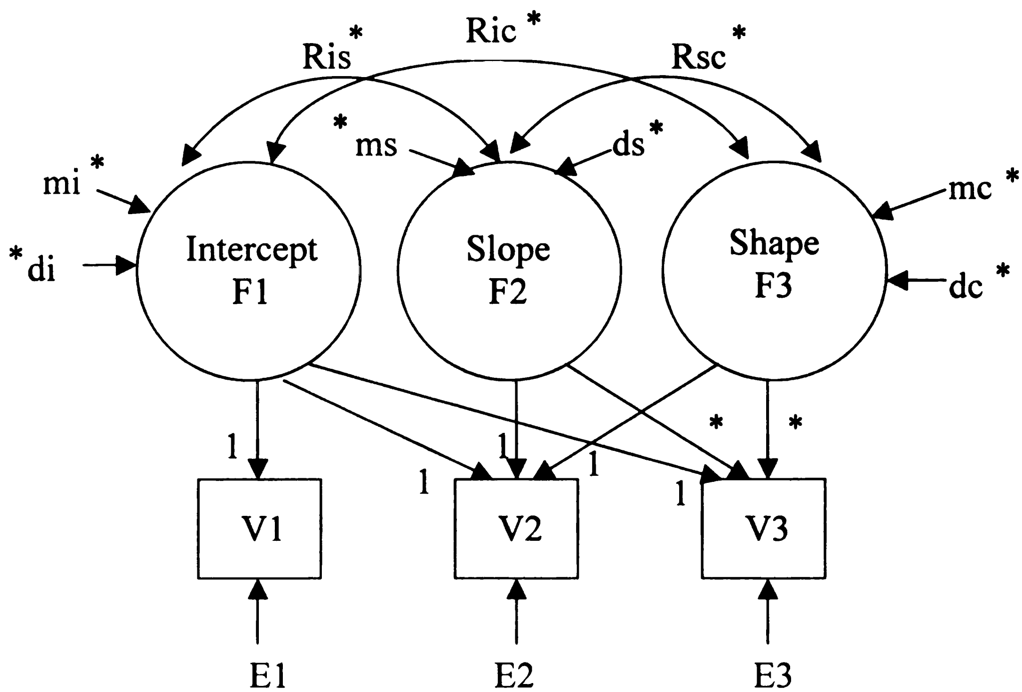
Linear growth can be modeled with two latent factors as shown in Figure 5.1. The first factor, F1, represents the intercept of the growth curve and the second factor, F2, represents the slope/shape of the curve. The manifest variables, v1, v2, v3, reflect the measurements taken at each point in time. Fixing the factor loadings from F1 to v1, v2, and v3 to 1.0 and to zero from F2 to v1, sets the starting point ("initial status" or intercept) of the growth trajectory curve. The factor loadings relating the manifest variables (v1, v2, v3) to the shape factor (F2) can be free or fixed, whichever best captures the functional form of the growth trajectory over the time points. The shape corresponds to the "rate of change" in the variable or the rate of increase or decrease over the time period modeled. For example, fixing the paths at from F2 to v1, v2, and v3 at 0, 1, and 2 respectively, represents linear growth. Freely estimating the path from F2 to v3 allows the shape of the trajectory to be determined by the data. Such a model is referred to as an unspecified two-factor model (Chan, 1998). In this type of model, the loadings plotted against the observed time interval gives a visual representation of the nature or shape of the change trajectory. The time points do not need to be equally spaced apart for LGC models but do require balanced data in that all individual data must have been collected at the same time. In this study, the time periods are spaced five months apart for reasons discussed in Chapter 3. The balanced data panel was achieved through the missing data imputation previously described.

Figure 5.1 Two-factor Polynomial Latent Growth Curve Model



Notes: v1, v2, v3 represent the same manifest variable at t=1, 2, 3, F1 is the latent variable intercept , F2 is latent variable slope, mi is the mean intercept, ms is mean slope, di is the intercept variance, ds is the slope variance. Ris is intercept-slope covariance.

Figure 5.2 Three-factor Polynomial Latent Growth Curve Model



Three or more time points allow an opportunity to test for nonlinear trajectories (Duncan, et al., 1999). The LGC in Figure 5.2 demonstrates a quadratic function of the observed time metric. In this type of model, a third latent factor is added to represent the curvilinear trajectory. The paths from F3 to the manifest variables are set at 1, 2 and 4 to represent quadratic growth. The error variances can either be freely estimated or fixed at certain values and are often constrained to be equal across repeated measures. When the model is under-identified, the error variances are usually set to zero (Duncan, et al. 1999).

In LGCs, the means and variances of the latent variables are freely estimated. This is accomplished by evaluating the augmented moment matrix or using the V999 code within EQS (Bentler, 1995). The latent factors are allowed to covary as indicated by the double-headed curved arrow between factors. The mean of the intercept factor, m_i, is equal to the mean of the latent scores of the individual growth curves at time 1. Variables, m_s and m_c also model the group means for the latent factors, F2 and F3. The variances of the disturbances of the latent variables, d_1 and d_2, are equal to the variances of the latent factors themselves.

Standard assumptions of LGCs are: (a) the variance of the latent means is zero; $var(m_1) = var(m_2)$, (b) the variances of all latent variable have zero means, $E(d_1) = E(d_2) = 0$, (c) the means and variances of latent variables do not covary; $cov(m_1,m_2) = cov(m_1, d_1) = cov(m_1, d_2) = cov(m_2, d_1) = cov(m_2, d_2) = 0$, and (d) the error variances do not covary with each other or any variables except the measured variables they directly affect; $cov(E1, d_1) = cov(E2, d_1) = cov(E3,d_1) = cov(E1, d_2) = cov(E2,d_2) = cov(E3, d_2) = 0$.

Each of the constructs in the model defined in Chapter 2 was first tested under the univariate LGC to determine the shape of the change trajectory. In each case, a quadratic LGC was conducted first to determine if change followed an s-shaped growth[2]. In order to just identify the model in Figure 5.2 the error variances must be set to zero (Duncan, et al., 1999). The factor loadings are fixed at 1, 2, and 4 to model quadratic growth. The saturated nature of this model does not allow for testing of overall model fit using the standard model fit indices in structural equation modeling (CFI, NFI, RMSEA, etc.). With three repeated measures, there are 3 variances, 3 covariances, and 3 observed means and the model estimates 3 variances, 3 covariances, and 3 means for the intercept, slope, and quadratic latent factors, thus, representing 0 degrees of freedom. However, the test statistics for the three latent growth factors can be evaluated.

Table 5.7 shows the results of the EQS models run under maximum likelihood estimation. The only construct that was found to have a significant coefficient on the quadratic latent variable, F3, was the 'successful adoption of innovations'. Subsequently, the remaining constructs were tested under a linear growth model where F3 is eliminated as depicted in Figure 5.1. Unspecified two-factor models were run with the 'shape' path freely estimated.

Small sample size bias has been shown to be a problem in using fit indexes for evaluating goodness of fit statistics in SEM (Hu and Bentler, 1995). In evaluating the univariate growth models in several cases, CFI were evaluated at 1.0 with an RMSEA = 0.000, suggesting a perfect fit. In these instances, to better estimate the goodness of fit, simulations were conducted using bootstrapping with 150 cases and 5 replications in

[2] It is not possible to confirm an s-shaped growth with three data points. Only the quadratic trajectory can be tested.

EQS. The resulting fit parameters reported in Table 5.7 indicate if this simulation technique was used to estimate the fit indexes and parameter estimates.

In this table, the path from F3 to v3 is labeled 'time'. As can be seen from the factor loadings, all of the coefficients for this path have 90% confidence intervals that include 2.0. This indicates a linear growth trajectory over time for these constructs. Significant effects were found on the intercept and slope effects, F1 and F2, for all the constructs. Table 5.7 also reports the quadratic function factor loading for each construct although ultimately it was not modeled except for 'successful adoption of innovations'. Table 5.8 shows the variances and covariances of the latent variables. The estimate of the covariance between time 1 and 2 for the construct, 'NP program success' was the only one shown to be significant. This can be interpreted as the initial starting point determines the slope factor at time 1 for measuring NP program success. The positive correlation (0.559, $p \leqslant .05$) indicates that the higher the initial reported value for NP success the greater the rate of change over time.

5.5.2 Bivariate Linear Growth Curves

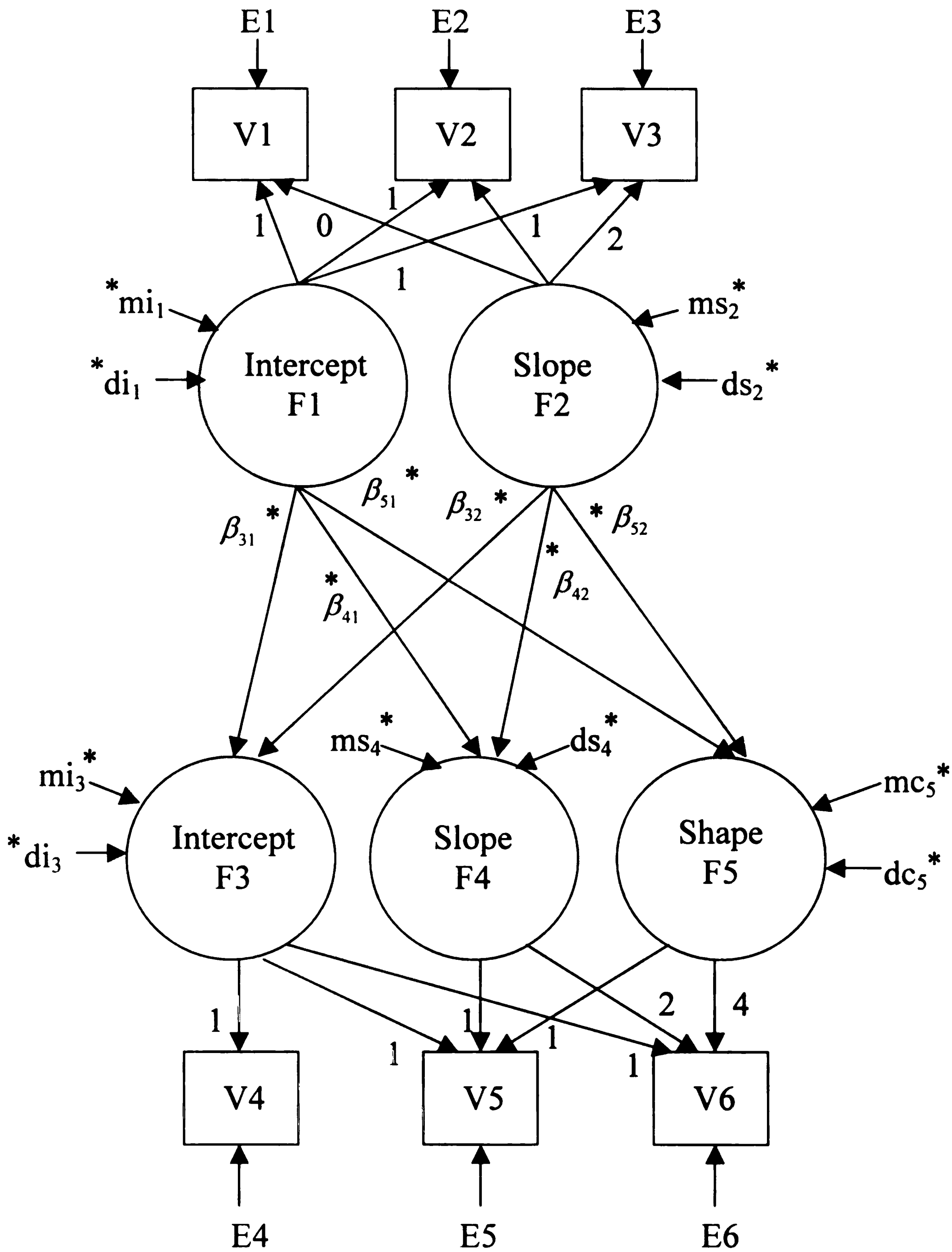
Multivariate latent growth models can be obtained by combining two or more univariate models. Bivariate models were used to test the hypotheses presented in Chapter 2 (replicated in Table 5.9 for convenience). As the name implies, bivariate modeling combines two LGCs in order to evaluate the effect of the change in one variable upon another. By regressing the intercept, slope and shape factor of one LGC upon another, the relationship between each other can be tested. The intercept, slope and shape factors have the same meaning as in univariate LGC modeling. An example of one of the bivariate models used in Study 2 is shown in Figure 5.3

The hypotheses presented in Chapter 2 propose specific growth trajectory relationships over time. If the hypothesis suggests nonlinear s-shaped growth, the dependent variable was modeled as a quadratic trajectory. If the hypothesis suggests a linear growth relationship between the constructs, the DV was modeled with a linear trajectory. The growth trajectory of the explanatory variable was set based on the univariate LGC and the growth trajectory for the dependent variable was set based on the hypotheses. For example, hypothesis 1 proposes a nonlinear relationship with the DV, successful adoption of innovations. The univariate analysis indicated that adaptive capacity is linearly growing over time. Thus, a linear growth model was used for the adaptive capacity's time trajectory and a quadratic model was used for the successful adoption of innovations' time trajectory to test the relationship between these constructs.

Figure 5.3 demonstrates the model used in M1, M2, M3, M7, M8, M10 and M11, which were created to test hypotheses H1, H2, H3, H7, H8, H10 and H11, respectively. Quadratic growth trajectories for both the antecedent and DV were used to model M4, M5, and M6. A quadratic LGC modeling the antecedent and a linear LCG for the DV were used for M3. Linear LGCs for both the antecedent and DV were used to model M9.

In a bivariate model, the paths between the endogenous factors, β_{ii}, and the means of the latent variables for the DV are of primary interest, and thus, are freely estimated. The results of the bivariate modeling are detailed in the next section.

Figure 5.3 Bivariate Linear Growth Curve Model Example



Notes: v1, v2, v3 represent the same measure at t=1, 2, 3, respectively, for variable A.
v4, v5, v6 represent the same measure at t=1, 2, 3, respectively, for variable B.

Table 5.7: Univariate Linear Growth Curve Results

	Adaptive Capacity	Slack[1] Resources	Marketing-R&D Integration	Successful Adoption of Innovations	Knowledge[1] Exploitation	Marketing Proficiencies	R&D[1] Proficiencies	NP[1] Program Success
CFI	0.994	0.995	0.986	1.00	0.992	0.983	0.985	0.989
NFI	0.987	0.984	0.974	0.994	0.978	0.971	0.972	0.980
RSMEA	0.128	0.060	0.156	0.012	.080	0.169	0.103	0.095
90% CI	(0.000, 0.425)	(0.000, 0.283)	(0.000, 0.357)	(0.000, 0.377)	(0.000, 0.312)	(0.000, 0.367)	(0.012, 0.306)	(0.016, 0.318)
Chi -square	$\chi_2^2 = 1.77$	$\chi_2^2 = 2.23$	$\chi_2^2 = 4.30$	$\chi_0^2 = 0.986$	$\chi_2^2 = 2.91$	$\chi_2^2 = 4.70$	$\chi_2^2 = 3.34$	$\chi_2^2 = 3.42$
λ_t, time	1.737 ** (0.164)	2.460** (0.201)	1.934** (0.150)	n.a.	1.780** (0.121)	1.933** (0.169)	1.778** (0.130)	1.983** (0.148)
mi, intercept	5.252** (0.173)	3.473** (0.204)	5.225** (0.167)	5.939** (0.118)	4.66** (0.155)	4.104** (0.181)	5.043** (0.171)	0.925** (0.165)
ms, slope	0.748** (0.093)	-0.256** (0.104)	0.556** (0.096)	1.269** (0.211)	0.935** (0.119)	0.492** (0.095)	0.834** (0.117)	0.537** (0.117)
mc, quadratic	-0.099 (0.063)	-0.074 (0.057)	0.059 (0.058)	-0.146** (0.068)	-0.092 (0.063)	0.031 (0.057)	-0.059 (0.064)	-0.045 (0.067)
Trajectory	Linear	Linear	Linear	Quadratic	Linear	Linear	Linear	Linear

** significant at $p \leq 0.05$

1. evaluated using simulation techniques

Table 5.8: Means and Variances of Univariate Models

	Adaptive Capacity	Slack Resources	Marketing-R&D Integration	Successful Adoption of Innovations	Knowledge Exploitation	Marketing Proficiencies	R&D Proficiencies	NP Program Success
Intercept var, di	1.418** (0.295)	1.961** (0.412)	1.235** (0.271)	0.665** (0.136)	1.007** (0.237)	1.460** (0.319)	1.295** (0.291)	1.194** (0.269)
Slope var, ds	0.392** (0.115)	0.496** (0.131)	0.293** (0.085)	2.143** (0.438)	0.426** (0.122)	0.288** (0.088)	0.448** (0.124)	0.524** (0.145)
Covar(di,ds), Ris	-0.112 (0.119)	-0.260 (0.157)	0.158 (0.100)	0.464** (0.185)	0.120 (0.113)	0.110 (0.108)	-0.110 (0.133)	0.442** (0.140)
Shape var, dc				0.221** (0.045)				
Covar(di,dc), Ric				-0.095 (0.057)				
Covar(ds,ds), Rsc				-0.592** (0.131)				

** significant at $p \leqslant 0.01$

Table 5.9 Hypotheses

H1: The relationship between a firm's adaptive capacity and its successful adoption of catalytic innovations follows over time a nonlinear path of S-shaped growth.

H2: The relationship between a firm's slack resources and its successful adoption of catalytic innovations follows over time a nonlinear path of S-shaped growth.

H3: The greater the marketing-R&D integration, the more successful the adoption of catalytic innovations into the firm.

H4: The relationship between a firm's successful adoption of catalytic innovations and its knowledge exploitation follows over time a nonlinear path of S-shaped growth.

H5: The relationship between a firm's successful adoption of catalytic innovations and marketing proficiencies in the new product development process follows over time a nonlinear path of S-shaped growth.

H6: The relationship between a firm's successful adoption of catalytic innovations and R&D proficiencies in the new product development process follows over time a nonlinear path of S-shaped growth.

H7: The relationship between a firm's knowledge exploitation and new product development program success follows over time a nonlinear path of S-shaped growth.

H8: The greater the marketing proficiencies, the greater the success of the firm's new product development program.

H9: The greater the R&D proficiencies, the greater the success of the firm's new product development program.

H10: The relationship between a firm's new product development program success and its adaptive capacity follows over time a nonlinear path of inverted S-shaped growth.

H11: The relationship between a firm's new product program success and slack resources follows over time a nonlinear path of S-shaped growth.

5.6 Results

The results of the bivariate analyses are shown in Tables 5.10-5.13. Except for M4, all of the models tested showed CFIs and NFIs greater than or equal to 0.900, which indicated a good fit (Bentler, 1995). The RMSEAs ranged from 0.043 to 0.208 (excluding M4). Except for M4 and M6, the RMSEA 90% confidence intervals included 0.05, the maximum cutoff suggested for this goodness-of-fit criteria (Browne and Cudeck, 1993). Overall, the models show very good fit to the bivariate LGC model. In order to evaluate Akaike's Information Criteria (AIC). Each model was also compared to a null model (H0) where no relationships between constructs existed. The lower the AIC, the better the fit of the model. In all cases, the AIC was consistent with the fit indices. All indices are reported in Tables 5.10-5.13.

The intent of this study was to evaluate how the dynamic nature of a variable may affect a dependent variable over time. In order to test this type of relationship, paths were established from the intercepts, slopes and shapes (curvatures) of one LGC to another LGC. For a hypothesis to be supported, at least one of the β paths linking the LGCs to the other must be significant, <u>and</u> secondly, the means of the intercept, slope and/or shape factor of the dependent variable must be significant to show that the model follows the trajectory modeled. If both criteria are not achieved, there is no support for the relationship.

Time effects must be taken into consideration when interpreting significant relationships in bivariate LGCs. Intercepts indicate time1 status, slopes indicate the rate of growth (or decay) over the time frame between data collections, and shapes indicate any change in growth direction over time. A few of the β paths established in Figure 5.3 are interpreted as follows:

(a) intercept → intercept ($\beta_{i1,i2}$): the 'initial status' (starting point) of a dependent variable is affected by the initial status of the explanatory variable. A positive β indicates the higher (lower) the values at t=1, the higher (lower) the value of the DV at t=1. A negative β indicates the higher (lower) the start values at t=1, the lower (higher) the initial value of the DV at t=1.

(b) slope → slope ($\beta_{s1,s2}$): the rate of change of a dependent variable is affected by the rate of change of the explanatory variable. A positive relationship indicates that the faster a variable is changing over time (change may be + or -) the faster the change in the DV(change can be + or -). Thus, the rate of change of the DV becomes amplified or dampened due to the effect of the explanatory variable.

(c) intercept → slope ($\beta_{i1,s2}$): the initial status of an explanatory variable affects the rate of change of the DV. A positive relationship indicates a greater growth rate and a negative relationship indicates a dampen growth rate. For example, a negative relationship indicates that higher initial levels of a variable result in *less* steep growth trajectories in a positively growing DV. This negative relation does not indicate a decrease in the DV over time but instead implies smaller rates of positive change.

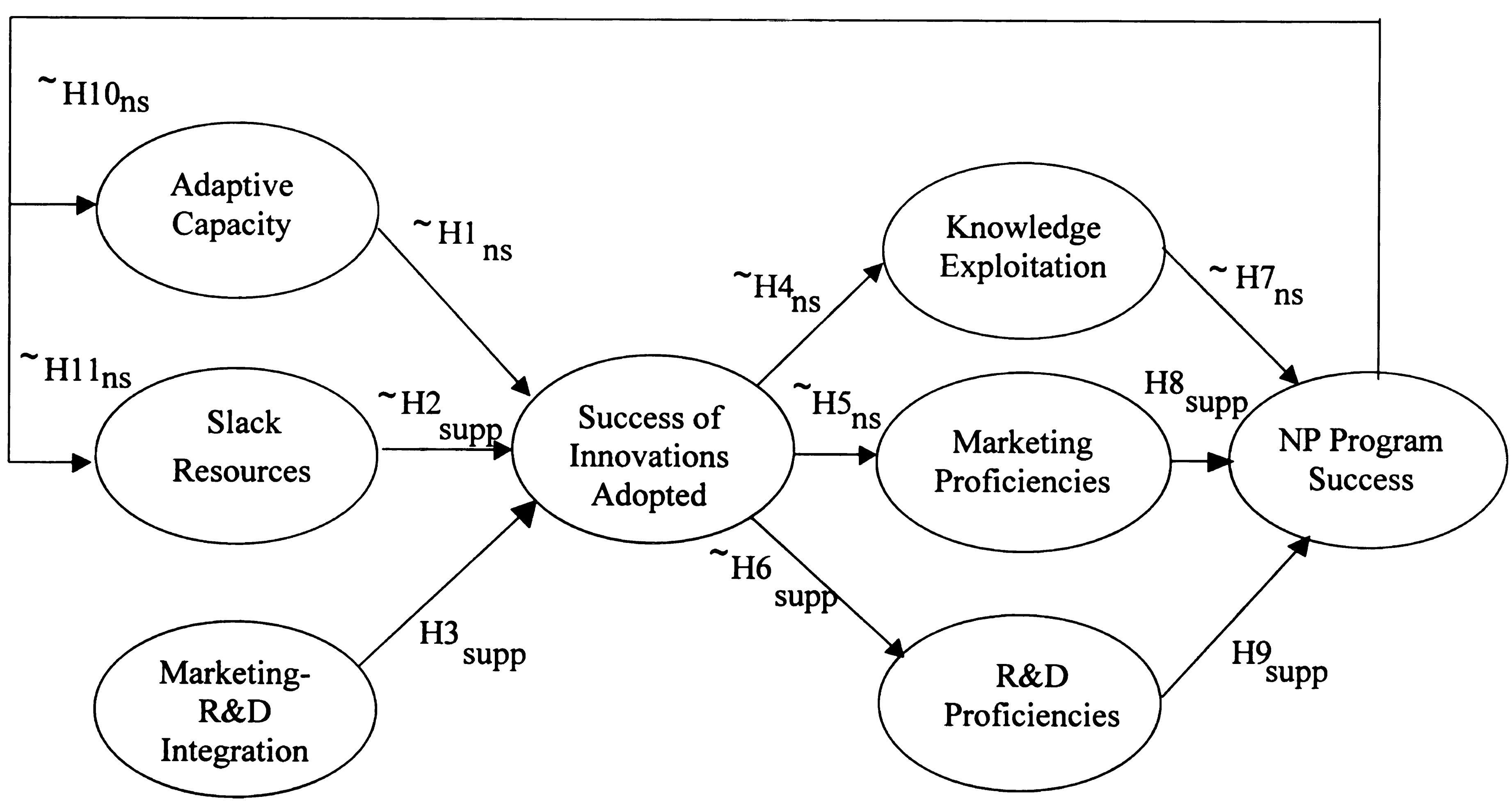
Figure 5.4 shows the model with the hypotheses and their outcome. Five of the eleven hypotheses were supported. H1, H4, H5, and H7 were not supported because either the paths, the means of the latent variables, or both were not significant. In M1, no paths between the LGCs were significant. For M4 and M7, at least one path between the

LGCs was significant except the mean on the shape (curvature) latent variable was insignificant suggesting a linear relationship opposed to the s-shaped relationship proposed in H4 and H7. In M5, although two paths were significant, none of the means of the DV were significant suggesting no relationship between the adoption of innovations and marketing proficiencies over time. Hypotheses H10 and H11 were also not supported and will be discussed later.

Support was found for H2, which proposes an s-shaped relationship between slack resources and the adoption of innovations. The means for the intercept, slope and shape for the DV, successful adoption of innovations, were all found to be significant (see Table 5.12). The mean of the shape factor has a negative coefficient ($m_c = -0.146$, $p \leq 0.05$), suggesting growth where a peak is achieved and a downturn occurs, possibly s-shaped[3]. In M2, significant relationships were found on two paths between LGCs (see Table 5.10). A negative relationship exists between the intercept of slack resources and the intercept of the successful adoption of innovations ($\beta_{i1,i2} = -0.182$, $p \leq 0.01$). The more slack resources available to the NP process at t=1, the lower the reported success in the adoption of innovations. However, the rate of change in the availability of resources for NP projects was *positively* related to the intercept of the successful adoption of innovations ($\beta_{s1,i2} = 0.235$, $p \leq 0.05$). These two effects drive the intercept in opposite directions with the slope effect possibly being greater.

In M3, support was found for the linear relationship between marketing-R&D integration and the adoption of innovations as proposed in H3. First the means for the intercept and slope factors for the DV were positive and significant ($m_i = 5.227$, $p \leq 0.01$;

Figure 5.4 Model with Hypotheses



notes: ns = not supported; supp = supported

Table 5.10: Bivariate Linear Growth Curve Results, M1 -M6

	M1 Adaptive Capacity - Adoption of Innovations	M2 Slack Resources - Adoption of Innovations	M3 Marketing-R&D Integration - Adoption of Innovations	M4 Adoption of Innovations - Knowledge Exploitation	M5 Adoption of Innovations - Marketing Proficiencies	M6 Adoption of Innovations - R&D Proficiencies
CFI	0.972	0.991	0.998	0.898	0.942	0.938
NFI	0.938	0.956	0.965	0.871	0.900	0.912
RSMEA	0.127	0.076	0.043	0.256	0.162	0.208
90% CI	(0.000, 0.214)	(0.000, 0.175)	(0.000, 0.157)	(0.179, 0.331)	(0.087, 0.232)	(0.124, 0.289)
Chi -square	$\chi^2_{11} = 19.28$	$\chi^2_{11} = 13.85$	$\chi^2_{11} = 11.75$	$\chi^2_{12} = 46.23$	$\chi^2_{15} = 33.68$	$\chi^2_{10} = 30.49$
AIC	-2.72	-8.15	-10.25	-8.51	3.68	10.49
AIC (H0)	-5.12	-3.28	-8.67	-28.0	6854.6	93.01
βs	n.s.	$\beta_{i1,i2} = -0.182$*** (0.071) $\beta_{s1,i2} = 0.235$** (0.118)	$\beta_{s1,s2} = 0.411$** (0.197)	$\beta_{c1,i2} = 16.66$*** (1.69) $\beta_{s1,s2} = 0.453$*** (0.092)	$\beta_{c1,i2} = 17.83$** (1.81) $\beta_{s1,s2} = 0.177$* (0.099)	$\beta_{i1,i2} = 0.480$** (0.191) $\beta_{c1,s2} = 4.966$* (2.03) $\beta_{s1,c2} = 0.143$* (0.025)
Hypotheses	H1: not supported	H2: supported	H3: supported	H4: not supported	H5: not supported	H6: supported

***significant at $p \leqslant .10$; ** significant at $p \leqslant 0.05$; *** significant at $p \leqslant 0.01$; β subscripts: i1=intercept on antecedent, i2=intercept on DV; s1=slope on antecedent, s2=slope on DV; c1=shape (curvature) on antecedent, c2=shape on DV; H0: no relationships modeled**

Table 5.11: Bivariate Linear Growth Curve Results, M7 -M11

	M7 Knowledge Exploitation - NP Program Success	M8 Marketing Proficiencies - NP Success (linear)	M9 R&D Proficiencies - NP Success (linear)	M10 NP Program Success - Adaptive Capacity	M11 NP Program Success - Slack Resources
CFI	0.990	0.995	0.993	0.972	0.965
NFI	0.969	0.962	0.955	0.938	0.942
RSMEA	0.101	0.058	0.066	0.127	0.172
90% CI	(0.000, 0.216)	(0.000, 0.160)	(0.000, 0.165)	(0.003,0.210)	(0.077, 0.261)
Chi -square	$\chi^2_7 = 10.29$	$\chi^2_{12} = 13.66$	$\chi^2_{12} = 14.25$	$\chi^2_{12} = 21.04$	$\chi^2_{10} = 21.55$
AIC	-3.71	-10.33	-9.74	-2.67	3.55
AIC(H0)	-3.94	-4.90	-8.97	10.0	10.0
βs	$\beta_{i1,s2}$ = -0.275* (0.140)	$\beta_{i1,i2}$ = 0.235* (0.118) $\beta_{s1,s2}$ = 0.419** (0.166)	$\beta_{s1,s2}$ = 0.356** (0.159)	$\beta_{i1,i2}$ = 0.458** (0.136) $\beta_{i1,s2}$ = -0.154* (0.073) $\beta_{s1,s2}$ = 0.417** (0.115)	$\beta_{i1,i2}$ = -0.654*** (0.161) $\beta_{s1,s2}$ = 0.526*** (0.149) $\beta_{i1,c2}$ = 0.085*** (0.023)
Hypotheses	H7: not supported	H8: supported	H9: supported	H10: not supported	H11: not supported

***significant at $p \leqslant .10$; ** significant at $p \leqslant 0.05$; *** significant at $p \leqslant 0.01$; β subscripts: i1=intercept on antecedent, i2=intercept on DV; s1=slope on antecedent, s2=slope on DV; c1=shape (curvature) on antecedent, c2=shape on DV; H0: no relationships modeled**

Table 5.12: Means and Variances of Bivariate LGC Model for Dependent Variable, M1-M6

	M1	M2	M3 (linear)	M4	M5	M6
Intercept, mi	5.606*** (0.529)	6.589*** (0.276)	5.227*** (0.512)	7.056*** (1.17)	2.183 (1.829)	2.080* (1.147)
Slope, ms	1.146*** (0.238)	1.340*** (0.210)	1.048*** (0.237)	0.344** (0.171)	0.194 (0.165)	1.529*** (0.439)
Shape,mc	-0.146** (0.068)	-0.146** (0.068)	—	-0.046 (0.032)	0.010 (0.030)	-0.210*** (0.048)
var (intercept), di	0.647*** (0.133)	0.570*** (0.118)	.005	.005	0.607 (1.407)	1.097*** (0.257)
var (slope), ds	1.268*** (0.325)	2.026*** (0.421)	0.689 (0.492)	0.550*** (0.113)	0.394*** (0.102)	.005
var (shape), dc	.005	0.213*** (0.045)	0.055 (0.054)	0.046*** (0.010)	.005	.005
covar(di,ds), Ris	0.474*** (0.183)	0.392*** (0.167)	1.403*** (0.328)	0.244*** (0.099)	0.089 (0.132)	n.s.
covar(di,dc), Ric	-0.099* (0.056)	-0.094* (0.053)	-0.410*** (0.099)	n.s.	-0.043 (0.037)	-0.055*** (0.022)
covar(ds,dc), Rsc	-0.160*** (0.059)	-0.571*** (0.129)	-0.113 (0.157)	-0.107*** (0.028)	-0.028* (0.017)	n.s.

* significant at $p \leq 0.10$
** significant at $p \leq 0.05$
*** significant at $p \leq 0.01$
n.s. = not significant, therefore not modeled in

Table 5.13: Means and Variances of Bivariate LGC Model for Dependent Variable, M7-M11

	M7	M8	M9	M10	M11
Intercept , mi	1.479* (0.780)	-0.047 (0.509)	0.746*** (0.258)	4.834*** (0.198)	4.147*** (0.248)
Slope, ms	1.625*** (0.532)	0.396*** (0.128)	0.313** (0.161)	0.417*** (0.115)	-0.469*** (0.164)
Shape, mc	-0.023 (0.034)	—	—	-0.082** (0.039)	-0.151*** (0.065)
var (intercept), di	1.057*** (0.302)	1.103*** (0.246)	1.162*** (0.269)	1.149*** (0.236)	1.908*** (0.391)
var (slope), ds	0.333* (0.188)	0.448*** (0.111)	0.453*** (0.115)	0.327*** (0.069)	0.750*** (0.178)
var (shape), dc	.005 (0.0150	—	—	0.044*** (0.009)	0.007 (0.012)
covar(di,ds), Ris	0.496*** (0.201)	0.383*** (0.125)	0.426*** (0.134)	n.s.	-0.553*** (0.207)
covar(di,dc), Ric	-0.0.014 (0.053)	—	—	n.s.	0.131* (0.077)
covar(ds,dc), Rsc	-0.005 (0.043)	—	—	n.s.	-0.071 (0.044)

* significant at $p \leq 0.10$
** significant at $p \leq 0.05$
*** significant at $p \leq 0.01$
n.s. = not significant therefore not modeled in

$m_s = 1.048$, $p \leq 0.01$). Secondly, a positive and significant relationship exists 0.01; $m_s = 1.048$, $p \leq 0.01$). Secondly, a positive and significant relationship exists between the slope factors of these two constructs ($\beta_{s1,s2} = 0.411$, $p \leq 0.05$). This indicates the greater the change in integration activities, the greater the rate of change in the successful adoption of innovations.

Hypothesis 6, proposing that the successful adoption of innovations result in a non-linear s-shaped growth trajectory for R&D proficiencies, was marginally supported. Although CFI and NFI passed goodness of fit criteria (CFI = 0.938, NFI = 0.912), RMSEA did not, RMSEA = 0.208, 90%CI = (0.124, 0.289). The high RMSEA appears to be the result of the marginally significant β coefficients[4]. Both tests for significance were passed. The means of the intercept and slope of the DV were significant ($m_i = 2.08$, $p \leq 0.10$, $m_s = 1.529$, $p \leq 0.01$, $m_c = -0.210$, $p \leq 0.01$) and three β paths were found to be significant. In M6, the intercept means were positively related ($\beta_{i1,i2} = 0.480$, $p \leq 0.05$), the curvature factor mean from the successful adoption of innovations to the slope of R&D proficiencies was positive ($\beta_{c1,s2} = 4.966$, $p \leq 0.10$), and the slope factor mean of the antecedent positively affected the curvature mean of the DV ($\beta_{s1,c2} = 0.413$, $p \leq 0.10$). Thus, the intercept, slope and curvature factor means of the DV were affected by the growing explanatory variable.

An interesting effect found in M6 is that in the univariate analysis, the mean quadratic factor was insignificant for R&D proficiencies (-0.059, n.s.), but when

[4] High RMSEAs appear to be characteristic of many LGC models. Researchers have questioned the appropriateness of fit indices in the context of linear growth curve models, (c.f. Kaplan 1998, SEMNET discussion, 12/21/98). High RMSEAs may not be indicative of poor fit. AICs may be better indicators of best fitting models.

regressed upon the successful adoption of innovations the mean becomes highly significant (-0.210, $p \leq 0.01$). This suggests that the R&D proficiencies follow a nonlinear trajectory when affected by the successful adoption of innovations.

Both H8 and H9 were supported. For M8, the resulting mean intercept for the DV, NP program success was not significantly different from zero (scale –3 to +3) and the slope mean was 0.396, $p \leq 0.01$ (see Table 5.13). For M9, mean intercept for the DV was 0.746, $p \leq 0.01$, and the slope mean was 0.313 $p \leq 0.05$.

In testing the β paths, the initial starting point for marketing proficiencies was related to the initial starting point reported for NP program performance (M8: $\beta_{i1,i2}$ = 0.235, $p \leq 0.10$). The greater the proficiencies at t = 1, the greater the NP program performance reported at time 1. In both M8 and M9, the slopes between the LGCs were positive and significant (M8: $\beta_{s1,s2} = 0.419$, $p \leq 0.05$; M9: $\beta_{s1,s2} = 0.356$, $p \leq 0.05$). This indicates a positive relationship whereby the faster that proficiencies grow (or decay), the faster the growth (or decay) in NP program success. It is interesting to note that in the univariate analysis, NP program success's slope mean was 0.537 ($p \leq 0.05$). However, when regressed upon marketing proficiencies the slope decreased from 0.537 ($p \leq 0.05$) to 0.396 ($p \leq 0.01$) and when regressed upon R&D proficiencies the slope decreased to 0.313 ($p \leq 0.05$). This suggests slower growth when the effects of proficiencies are considered.

Although M10 found evidence to support a nonlinear relationship between NP program success and adaptive capacity, H10 was not supported. H10 proposed an inverted relationship where as NP success increases, adaptive capacity decreases. This growth trajectory was not found. Hypothesis 11 was also not supported as it followed an inverted relationship that was not proposed! Even though the hypotheses were not supported, the M10 and M11 demonstrate interesting characteristics. For both adaptive capacity and slack resources, univariate LGCs indicate linear growth trajectories for these variables. However, when regressed upon NP program success, they both take on a quadratic growth trajectory where a peak is reached and a shift in trajectory direction occurs.

In M10 the intercept, slope, and shape means were all significant ($m_i = 4.834$, $p \leq 0.01$, $m_s = 0.417$, $p \leq 0.01$, $m_c = -0.082$, $p \leq 0.05$), see Table 5.13. M10 showed a positive relationship between the intercepts of NP program performance and adaptive capacity. The higher the initial status of NP program success, the higher the reported intercept for adaptive capacity ($\beta_{i1,i2} = 0.458$, $p \leq 0.05$), see Table 5.11. A negative relationship exists between the initial status of NP program success and the slope of adaptive capacity ($\beta_{i1,s2} = -0.154$, $p \leq 0.10$). This indicates that higher initial levels of NP program success reported are associated with *less* steep (but still positively increasing) growth trajectories in adaptive capacity over time. This negative relation does not indicate a decrease in adaptive capacity over time but instead implies that higher initial levels of NP program success are associated with smaller rates of positive change in adaptive capacity.

As a DV, slack resources showed an inverted s-shaped relationship (M11). It has a positive intercept ($m_i = 4.147$, $p \leq 0.01$), a negative slope ($m_s = -0.469$, $p \leq 0.01$), and a negative mean curvature ($m_c = -0.151$, $p \leq 0.01$). A negative relationship exists between the intercept on NP program success and its initial status on slack resources

($\beta_{i1,i2}$ = -0.654, p $\leq$ 0.01). The higher the initial status reported for NP success, the lower the reported availability of slack resources. Yet, a *positive* relationship exists between the *rates of change* between these two variables. The greater the rates of change in NP program success, the greater the positive rate of change in slack resources ($\beta_{s1,s2}$ = 0.526, p $\leq$ 0.01). A positive relationship was also found on the β coefficient linking the intercept factor of NP program success and the shape factor of slack resources ($\beta_{i1,c2}$ = 0.085, p $\leq$ 0.01). M6 was the only other model that showed significant paths to all three latent factors of the dependent variable.

5.7 Conclusions

Despite only finding support for five of the eleven hypotheses many of the concepts introduced in Chapters 1 and 2 were supported. First, although adaptive capacity was not found to be an explanatory variable to the successful adoption of innovations, it *was* found to be affected by NP program performance. However, a positive relationship was revealed as opposed to the negative relationship proposed. Extant literature has suggested that as firms become more successful, they can become more rigid in structure (Miller, 1990; Leonard-Barton, 1992; Christensen, 1997). This was not found in the time frame studied here. Adaptive capacity followed a positively growing quadratic trajectory and NP program success a positive linearly growing trajectory when regressed upon each other. The bivariate analysis showed that as the rate of change of NP program success increased, the rate of change in adaptive capacity also grew. NP managers may become more flexible and adaptive to changes in the environment when NP success rates are increasing. Firms may see their success due to addressing the changing needs of the marketplace and continue to open themselves to meeting market requirements.

Secondly, support was found for slack resources and a marketing-R&D integration as explanatory variables for the successful adoption of innovations into the NP process. Greater rates of change in marketing-R&D integration are associated with greater positive rates of change in the adoption of innovations. This suggests that the adoption of innovations within a firm may possibly be more successfully integrated into the firm when both the marketing and R&D/engineering departments are involved. When marketing issues become part of the evaluation process for the adoption of innovations the potential for its successful implementation within the firm increases.

In regards to operationalizing the construct, 'marketing-R&D integration', it is important for researchers to recognize that many technologically oriented firms do not have formal marketing departments or if they do, marketing personnel may not interact with engineering personnel. This does not mean that the engineering department does not consider marketing issues during the NPD process. Measurements for this construct should reflect this situation.

Thirdly, only at t=1 was a relationship found between slack resources and innovation adoption success. The negative relationship observed is consistent with the notion of 'slack ' resources allowing greater failures in the innovation process (Levinthal and March, 1981). Slack resources are necessary to support failures in product development that are inherent in engineering driven firms. However, this study also found that an unlimited supply of resources will not necessarily lead to wildly successful adopted innovations as success appears to reach a saturation point as the observed quadratic trajectory suggests.

Lastly, this study provides empirical evidence that the adoption of innovations can be used indirectly as a strategic opportunity for a firm to build competences in the NP process. As a predictor variable, the successful adoption of innovations was found to have a positive effect on exploitation of technological knowledge (M4) and on R&D proficiencies (M6). Additionally, both knowledge exploitation and R&D proficiencies were found to be positively related to NP program performance success (M7 and M9). The adoption of innovations may be an overlooked strategy by NP managers (or at least NP researchers) for driving the success of the NP program. It is important to make the distinction that it is the knowledge embedded in the adopted innovation that can become embodied as successful new products. The adoption of innovations into a firm does not itself drive NP success. Firms may benefit from actively evaluating the innovations they adopt to ensure that it can effectively integrate the innovation into the NP process. Knowledgeable personnel as well as an 'innovation champion' may help to attain the highest knowledge yield from adopted innovations.

The major goals of study 2 were to gain a better understanding of the dynamic NP process and to determine if major components of the NP process were nonlinearly related. The result of this study show that the adoption of innovations may be one way to build NP process proficiencies, and indeed when time is taken into consideration, the relationships are nonlinear.

CHAPTER 6

CONTRIBUTIONS, LIMITATIONS AND FUTURE RESEARCH

6.1 Introduction

The primary objectives of this dissertation were two-fold: (1) to advance the practitioner's understanding of how adopted innovations can assist NP managers in driving the success of inventions, and (2) to advance the methodological framework of how the NP development process of technological firms can be studied as a dynamical system. A secondary question was to determine if 'catalytic' innovations significantly increase the success of an NP program. These questions and several others were set forth in Chapter 1. The answer to these questions a summary of the findings from studies 1 and 2 are presented in this chapter. Study 1, detailed in Chapter 4, used case studies and system dynamics modeling to test the relationships between the constructs as defined in Chapter 2. Study 2, detailed in Chapter 5, used a longitudinal repeated measures design to test the relationships between constructs using linear growth curve methodology in EQS.

6.2 Research Questions Addressed and Contributions

The first set of research questions presented in Chapter 1 addressed practitioner issues.

PQ1. Can the adoption of innovations into the firm contribute to the success of new products?

(i) Can the adoption of innovations act as a catalyst to the successful invention of new products?

(ii) **Does the successful adoption of technological innovations lead to an increase in the number of new product development projects undertaken by the firm?**

(iii) **What resources and types of organizational cultures (adaptive/rigid, integrated/decentralized marketing-R&D departments, scarce/unlimited resources) promote the successful adoption of innovations into the firm?**

The intent of this dissertation was to investigate the infusion effects of the successful adoption of innovations on the NP process. Studies 1 and 2 both addressed the overall question presented in PQ1. It was found in both studies that the successful adoption of innovations into the firm has an indirect effect on the success of a NP program. Innovations successfully adopted into an organization have the effect of increasing a firm's competences in technology knowledge utilization (exploitation) and R&D proficiencies. These studies also reveal a positive relationship between technology knowledge exploitation and R&D proficiencies as explanatory variables to NP program success. Thus, indirectly the successful adoption of innovation can drive NP success by helping organizations to better utilize their technology knowledge competences.

An important relationship not originally proposed for study neither in the research questions nor in the research model, was how does the adoption of innovations affect the firm's knowledge base. As no studies have previously reported on the *effects* of adopting innovations for the purpose of improving the NPD process, this relationship did not become evident until after the case studies had been conducted. The case studies revealed that firms accumulate knowledge banks that are utilized to develop new products. Without the proper knowledge stock in place, the firm cannot develop competitive products for the marketplace. Just one method of continually renewing the knowledge stock is through the adoption of innovations. Although March (1991) and Levinthal and March (1993) allude to the need to continually renew a knowledge base, these concepts have not previously been applied to the NP process or to the role that the adoption of innovations can play in this knowledge maintenance process.

The notion that technological knowledge requires 'management' by innovation-centric organizations was also revealed. As knowledge becomes outdated it may need to be 'shelved' as its usefulness in creating competitive products declines. However, utilizing 'new' knowledge may not always be optimal, as a firm may not have the opportunity to build engineering and manufacturing competences if it is continually evaluating and integrating new knowledge into the organization. The management of 'new' and 'old' knowledge and exploitation of aging knowledge may be important strategies for NP managers. It is possible that radical inventions require newer knowledge banks compared to the development of incremental inventions that can be developed using older knowledge. Knowledge management in the NP process is an area for future research.

Sub-issue (i) presented in PQ1 concerns the role of the 'catalytic' innovations in the NP process. The first question that must be asked is whether 'catalytic' innovations actually exist. 'Catalytic' innovations were previously defined in Chapter 1 as innovations adopted into the organization that act as a catalyst to develop new inventions not previously planned prior the adoption of the innovation. Marginal support was found for the existence of 'catalytic' innovation in the sample population studied. Respondents of the longitudinal study were asked to identify three innovations that had been adopted into their organizations within the past 36 months. Respondents were then asked to respond to the following question: "This innovation has allowed us to build new products we had not previously considered prior to its adoption". At time 1, the mean response to this question was 5.47 ($\sigma = 1.24$) based on a Likert scale of 1 to 7 with 7 being 'strongly agree'. Twelve of the 49 (24.5%) respondents rated this item at the highest scale. In the system dynamics model, sensitivity analyses found little evidence of 'catalytic' innovations effects NP program success. Together these findings show some support for the existence of catalytic innovations. Yet they should not be taken as conclusive evidence that 'catalytic' innovations do or do not exist. The firms in the study may not have reported on innovations that have significantly altered their NP strategy or may not be able to recognize these types of innovations. More likely, 'catalytic' innovations, like radical innovations are rare (Garcia and Calantone, 2002), and are not easily observable. Historical studies on the development processes of radical innovations may be a better method for studying catalytic innovations. This is an area for future research.

Sub-issue (ii) of PQ1 questions whether the successful adoption of innovations can lead to an increase in the number of new product projects undertaken by the firm. As previously discussed, the renewal of a firm's technology stock is an outcome of the successful adoption of innovations. Consequently, the greater the firm's technology stock, the greater its ability to undertake more new NP projects. The availability of knowledge stock does not guarantee more NP projects; it just enables the firm to develop more new products if other resources, such as personnel and capital, are available.

Sub-issue (iii) addresses which factors drive the successful adoption of innovations. The suggested predictors were adaptive capacity, marketing-R&D

integration, and slack resources. Both studies 1 and 2 found no support that a firm's adaptive capacity affects it ability to successfully integrate an adopted innovation into the firm. The case studies revealed that adaptive capacity might in fact be a moderator to knowledge utilization. Firms that can more easily adapt to dynamic environments are more likely to make use of 'new 'technological knowledge compared to firms that have lower adaptive capacities. Subsequently, adaptive capacity was modeled as an amplifier to the utilization of 'old and 'new' knowledge stocks in the SD model. Sensitivity analyses showed that adaptive capacity had relatively small effects on both success of adopting innovations and NP program success.

Study 2 was consistent with Study 1 in revealing that adaptive capacity is probably not an explanatory variable to the adoption of innovations. Study 2 *did* show a positive relationship between a firm's NP program succss and it adaptive capacity. The greater the NP success reported by a firm, the greater its rate of growth over time in adaptive capacity. This was contradictory to the proposed relationship suggesting that the more successful a firm becomes, the more rigid it becomes to new ideas (Leonard-Barton, 1988). As adaptive capacity is a new construct to marketing/NP literature, further theoretical and empirical analyses are needed to better define its role in the NP process.

The second explanatory variable studied was marketing-R&D integration. The empirical results of the longitudinal study showed that the greater the growth in inter-departmental integration, the greater the growth in the successful adoption of innovations. The more consideration given to marketing issues in the NP process, the better the assimilation of an innovation in to the firm. As previously noted in Chapter 5, marketing and R&D integration does not necessarily mean a structured interaction between departments. Many of the engineering companies in this study do not have formal marketing departments, yet they consider marketing issues when developing new products.

The third explanatory variable to the successful adoption of innovations, slack resources, has been noted to be a necessary but not sufficient criteria for allocating resources to innovation activities (Cyert and March 1963, Rosner, 1968). The results of the system dynamics model lent support for this theoretical concept. The number of innovations adopted into the firm was highly sensitive to the amount of slack resources available for these types of activities. A lack of resources resulted in fewer adopted innovations, which resulted in fewer new products.

A different effect was found in study 2. The initial status of slack resources reported at t=1 had a *negative* effect on the initial status of success in adopting innovations at t=1. So, the greater the resources available, the less the success at adopting innovations the was firm reported. These results add to the contradictory results obtained from previous empirical studies on the role of slack resources in the adoption of innovations (cf. Dewar and Dutton (1986) showed a positive relationship, and Damanpour (1991) showed no relationship). The previous studies had looked at individual innovations. This current study is unique from these previous studies in that it considered the NPD process for more than one innovation and at the program level. This wholistic approach may lead to the negative effect observed. On the program level, greater slack resources allow the firm to be more innovative and adopt more innovations, which ultimately lead to greater failures. Overall, even though greater slack resources lead to more individual innovation successes, they lead to more failures when considered at a program level. This negative relationship is supported by Levinthal and March (1993) who contend that slack resources allow the firm more opportunities to fail in NP development.

PQ2. How should firms structure themselves to increase the successful adoption of innovations?

A summary of the findings from PQ1 will also answer PQ2. Technologically oriented organizations that are interested in using the adoption of innovations as a strategy for driving greater success in their NP program should focus on making resources readily available to the NP process, encourage failures in NP design and actively involve marketing in the NP process. An important finding from both studies was that adopting innovations can increase technological knowledge competences. However, the quadratic trajectories observed in study 2 suggest that peaks in performance are often reached. The <u>continual renewal</u> of knowledge is important in the NP development process. Firms that structure themselves to be open to new knowledge will benefit not only in their success of adopting innovations but also in NP program performance.

PQ3. What effect does the successful adoption of innovations have on the lock-in (core rigidities) and lock-out of knowledge?

This question was addressed in Study 1 using the system dynamics model. Lock-in has been described as the phenomenon whereby a firm becomes so ingrained in a particular technology and knowledge base that it is unable to adapt to changing market conditions (Leonard-Barton, 1995). Leonard-Barton describes this as core competences evolving into core rigidities. A similar phenomenon is lock-out of knowledge, which is also closely related to 'absorptive capacity' (Cohen and Levinthal, 1990). Cohen and Levinthal argue that the ability to evaluate and utilize new knowledge is a function of the level of prior related knowledge. A firm must have an adequate foundation upon which to build new knowledge. A firm may lock itself out of the ability to acquire new knowledge for various reasons, which may include lack of appropriate personnel, complacency in the current status (lock-in), or simply poor managerial insights.

The effects of lock-in and lock-out from a knowledge perspective were examined in study 1. It was shown that firms that did not continually renew their knowledge stock lock themselves into old technological knowledge and lock themselves out of the ability to acquire new knowledge. A firm must have a knowledge foundation that is continually updated in order to be able to assimilate the latest technological knowledge. March (1991) referred to this as the balance between exploration and exploitation activities. Firms that do not continually take on exploration activities lock themselves out of new technology, whereby decreasing the firm's competitive advantage in developing new products (exploiting that knowledge base). The results of study 1 showed that firms that do not continually rebuild their knowledge stock eventually lose all competitive advantage and soon expire. As the adoption of innovations is one way of renewing the knowledge stock, lock-in and lock-out can be avoided by the continual adoption of innovations into the organization.

TQ1. Does a relationship exist between the adoption of innovations and the successful invention of new products in the technological firm? Are these relationships nonlinear?

The first part of TQ1 has been answered in responses to the previous questions. Strong evidence from both studies 1 and 2 showed that a positive relationship, although indirect, exists between the adoption of innovations and the successful invention of new products in the technologically oriented firm. What has not previously been addressed is the second part of TQ1. System dynamics modeling (study 1) creates differential equations to model the effects between constructs over time. Any nonlinear relationships are explicitly modeled in. Thus, it is not an appropriate methodology with which to answer this question.

Study 2 showed the existence of nonlinearities between many of the constructs not just between the adoption of innovations and NP program succss. As the focus of the study was on the change in variables over time, it is important to distinguish that time is an important factor in this study. It was found that a variable's growth trajectory over time may take on a significantly different picture when evaluated with respect to another dynamic variable.

For example at time 1 of the study 2, slack resources and NP program success are *negatively* correlated and highly significant ($r = -0.421$, $p \leq 0.005$). At time 2 there *is no relationship* ($r = -0.057$, $p = 0.70$) and at time 3 there is a marginally significant *positive* relationship (0.219, $p \leq 0.10$). Substantially different results about the relationship between slack resources and NP program success can be obtained based on when the data was collected. The linear/nonlinear growth curve analysis allows a more complete story to be presented. Slack resources follows an inverted quadratic trajectory over time ($\mu_{intercept} = 3.473$, $\mu_{slope} = -0.573$, $\mu_{curvature} = -0.089$, all significant at $p \leq 0.05$) when regressed upon NP program success. Yet, a *positive* relationship exists between the *rates of change* between these two variables. The faster NP program success changes over time, the faster the change in slack resources over time. During the data collection period, slack resources happened to be decreasing over time; thus, the faster NP program success grows, the faster slack resources become unavailable for NP activities. If slack resources had been growing over time, the positive relationship would indicate more resources become available as NP program success grows.

During the time of this study (July 2001-May 2002), the business environment for the United States was extremely turbulent. Many firms were re-strategizing due to the recession caused in part by the terrorist attack on New York City in September 2001. Taking this environment into account, it does not appear unreasonable that even though firms may have had increasing NP success, less slack resources were available for NP projects. Slack resources were being dedicated to other areas of the organization in order to weather the recession. The greater the success in new products meant that the NP program could sustain itself without additional dedicated resources, and therefore slack resources could be allocated to other programs in greater need.

Thus, the empirical analyses have found significant support for the existence of nonlinearities in the relationships studied.

TQ2. From a methodological perspective, does system dynamics modeling better represent the evolving new product development process compared to more traditional linear representations?

The intent of conducting two studies was to obtain two uniquely different perspectives of the dynamical NP process that could not be obtained through cross-sectional research designs. In hindsight, TQ2 is an inappropriate question, as no one methodology is 'better' than another. Each has its own advantages and disadvantages. As the limitations of each methodology will be explained in the next section, the advantages of the two methodologies in this study will be briefly examined here.

System dynamics (SD) modeling's primary advantage is its ability to simulate how a process evolves over time and how policies and decision rule changes may affect the goals inherent in the process. It allows the long-term impact of policy changes to be studied in a laboratory environment. Insights can be obtained that might not have been readily evident from methodological analyses that only allow short-term time periods.

SD modeling allows sensitivity analyses to determine important effects of changing, eliminating or adding a construct. Cross-sectional data collection and even longitudinal data collection does not allow for the collection of new data should a interesting concept appear during the course of the study. This was notable in this dissertation as knowledge was recognized as playing a more important role than originally modeled. As the longitudinal data collection had already been started it was not practical to try to collect the additional data required to evaluate this construct. Modeling a knowledge stock in the SD model was a much easier method of gaining a better understanding of the role of knowledge in the NP process.

SD modeling also provides an excellent opportunity for researchers to 'test out' the rationality and validity of their models prior to collecting data in the field. Simulations can test the internal consistency of a theory by ensuring that the behavior of the system theorized can in fact be generated by the underlying assumptions outlined (cf. Sastry, 1997). SD modeling also provides a 'laboratory' environment in which to discover implications of theoretical assumptions that may not be intuitively obvious (Sterman, 2000).

Additionally, current events have reinforced the increasing difficulties that researchers have in the collection of data through mail surveys. 'Testing' a model prior to collecting expensive primary data is extremely beneficial. Simulation techniques provide an excellent method for researchers to expand the knowledge base without gathering large quantities of data. Validation of the model still needs to occur with real world concurrence, thus simulation modeling can not eliminate the need to conduct fieldwork.

Longitudinal data also has its benefits despite the difficulty in obtaining balanced data sets. As previously demonstrated it can show a much more complete picture of a evolving process compared to cross-sectional data. Even though it usually is conducted under a much shorter time span than simulation models, it provides empirical support for what is actually occurring within a firm's NP process over a specific time frame. Chapter 5 provided an example on how to use linear/nonlinear growth models to analyze the dynamic NP process.

A different set of research questions can be asked when using longitudinal designs that cannot be addressed with cross-sectional data or even with system dynamics modeling. As Chapter 4 showed, the hypotheses introduced in Chapter 2 were not relevant to a system dynamics modeling approach. The hypotheses, which focused on the nonlinearities in the relationships between the constructs, also could not have been answered using cross-sectional data. When change itself is the object of study, the only way to investigate it is by using longitudinal data. Longitudinal studies allow nonlinearities between relationships to be tested.

A motivating factor for conducting this dissertation was to gain a better understanding of how firms evolve and adapt their organizational structure over time in order to effectively adopt innovations and produce inventions. To study the evolutionary nature of this process, longitudinal data must be used. Although simulation techniques have the advantage of being able to model extended time frames, actual data collection provides a picture of the changes actually taking place in the NP process of innovation-centric firms.

TQ3. Is adaptive capacity an antecedent to the successful adoption of innovations and how should it be operationalized?

Both studies showed little support for any relationship between adaptive capacity and the successful adoption of innovations. In study 1, adaptive capacity was modeled as an amplifier to marketing proficiencies, R&D proficiencies and technology knowledge utilization (exploitation). In conducting sensitivity analyses, it was found to have a limited effect on these constructs.

In study 2, adaptive capacity *was* found to be related to a firm's NP program success. The higher the initial status of NP program success, the higher was the reported adaptive capacity. A negative relationship exists between the initial status of NP program success and the slope of adaptive capacity ($\beta_{i1,s2}$ = -0.154). This indicates that higher initial levels of NP program success reported are associated with *less* steep (but still positively increasing) growth trajectories in adaptive capacity over time. This negative relation does not indicate a decrease in adaptive capacity over time but instead implies that higher initial levels of NP program success are associated with smaller rates of positive change in adaptive capacity. This finding supports the idea that the greater a firm's NP program success, the less flexible it becomes in being able to adapt to its environment. NP success can dampen the growth rate of adaptive capacity.

The relationship observed may have been a result of how the construct was operationalized. It was measured with four items (only three passed CFA analysis). Two were based on Jaworski and Kohli's (1993) market orientation measures and two were created for this study. The Cronbach alphas for the three measures were strong (t=1 α = 0.827; t=2 α = 0.761; t=3 α = 0.822) and an EFA revealed one factor. The three measures retained focused on a firm's flexibility in responding to customer's needs and competitors infringement on customers. Future research should retest the validity of the measures used to study this concept of a firm's ability, willingness and flexibility to adapt to its environment. Adaptive capacity does appear to be related to a firm's marketing orientation strategy and its NP program success.

6.2.1 Summary to Research Questions

These six research questions summarize the results of the two different methodologies used to study the infusion effects of the adoption of innovations on the evolving new product development process. System dynamics modeling emphasized the policy and decision making rules of the process whereas the longitudinal study examined the nonlinearities in the relationships of NP process attributes with respect to time. Each study provides unique contributions to the understanding of how the NP process changes over time. However, both studies were conducted within a limited scope, which will be discussed in the next section.

6.3 Limitations and Future Research

As previously noted, the two methodologies used in this dissertation have their distinct advantages, but they also have distinct disadvantages. System dynamics modeling simulates a process as established by the modeler. As the SD model developed was based on case studies of two small engineering firms (employees < 100), the process simulated reflects but a very small subset of the population of technologically oriented firms. Both of these firms did not have a marketing department that was actively involved in the NP development process. The role of marketing-R&D integration may have been more pronounced in the model if organizations that fully integrate these two departments had been studied. Although SD models should be verified with outside sources, they still reflect the perspective of the modelers.

Additionally, in building the SD model, boundaries were set that reflected only endogenous issues to the NP program. Exogenous issues such as environmental turbulence, competition and rate of technology change were not modeled into the system. These important factors can change the results of the decision making process within the NP process. One study, looking at the effects of competition, showed that the policies regarding resource allocation to research and development activities can be significantly altered based on competitive pressures (Garcia, et al., 2002). Effects of these types of exogenous factors should be modeled in future SD model based research.

Limitations to the longitudinal data analysis are similar to those for the system dynamics model. The sample was drawn from a unique set of small engineering driven companies (employees < 1000). These companies are all privately owned by a United States based parent company. Although allowed to maintain autonomy in many decisions, these companies must still report to corporate headquarters. Many of the companies also do not have a documented NP process in place. Fundamentally different results may have been obtained if the sample population had been large companies with more formalized NP programs.

Several of the companies participating in the longitudinal study were internationally located. The sample size was too small to conduct a multigroup analysis on the differences between the internationally based firms and the domestic located companies. The sample size (n = 49) also posed problems in obtaining goodness-of-fit indices for the confirmatory factor analysis and the univariate linear growth curves. A larger sample size would have allowed better evaluation of the goodness-of-fit of the model.

Linear growth curves (LGCs) require balanced data sets across the time frame studied. As longitudinal data is very difficult to obtain, this requirement of LGC necessitates missing data imputation. There is no ideal method for imputing data and future research should investigate the effects of using different imputation methods on the final results. Additionally, with data taken at only three time points, limitations exist on the types of growth trajectories that can be tested in LGC modeling. More data points across time would allow a more robust testing of the growth trajectories.

Utilizing SEM to evaluate linear growth curves is a relatively new methodological approach. It has primarily been used in psychology studies on individual growth rates. Curran (2000) writes that "it is important to note that the more complicated these growth models become, the greater the variety of ways there are to approach the model building strategy. There is not necessarily a right or wrong way to build and probe these models, but whatever steps are taken should be clearly articulated, well justified, and closely guided by the theoretical questions of interest" (pg. 27). This dissertation has used this guideline in building the models investigated. Future analyses of the use and interpretation of linear growth curves in modeling marketing/NP development issues will lead to a better understanding of this methodology.

6.3.1 Other Future Research

In addition to the suggestions for future research already noted, the results of this dissertation have facilitated thoughts for other research directions. The role of knowledge management in the new product development process, especially the use of 'old' and 'new' knowledge for building competitive products, should be further explored. The president of one of the case studies recently confined in me that he had recently realized the important role that older technology can play in the development of new products. He has vowed to investigate how he can use technology that had previously been shelved to revitalize his new product portfolio. Exploration and experimentation with newer technology would continue within the firm but would now take on different perspectives.

A potentially interesting study that developed from the system dynamic model would be to focus on resource allocation between exploration (research) and exploitation (development) activities. The outcome of the SD modeling provided some insights on how to balance these two distinctively different objectives. Future research in this area would help NP managers better understand when and how to allocate resources to R&D projects.

This dissertation has only alluded to the role of radical innovations in the NP process. However, this dissertation was motivated by an interest in learning how radical innovations 'emerge'. One thought was that catalytic innovations can cause a firm to take on a new perspective in designing new products that may result in radical innovations. This dissertation found little support for this proposition. This in itself is new knowledge gained, which can be used in future studies on the emergence of radical innovations.

It would be remiss not to add that future research should continue to look at the firm as an evolving system. System dynamics modeling and linear growth curves are just two methodologies for studying how processes change over time. This is an area rich with future research opportunities.

APPENDICES

APPENDIX A

APPENDIX B

APPENDIX C

APPENDIX A

Case Studies Supporting Documents

Table A.1 Case Companies' Descriptions

	Co. A	Co. B
Primary Business	Semiconductor Industry Suppliers	Welding Machines
Number of Employees:	75	15
Revenues:	less than 20 million	less than 5 million
Age:	30	10
Location:	Massachusetts, USA	New Jersey, USA
Sales Regions:	US, Korea, Europe, Japan	US, Canada
Engineering Staff:	10	2 + outsourcing
Sales & Marketing Staff:	5	2
Formal NPD Process:	No	No

Guidelines for Semi-Structured Interview for Study on the Infusion Effects of Technological Innovations on the New Product Development Process

Goal of research: The intent the of the interviews was to determine how technology-based firms use new-to-the-firm technologies to invent new products. Why innovations are adopted and how they are utilized within a firm were key points to understand. The qualitative data gathered was used as input to the written survey and a systems dynamics model.

Methodology: Interviews were arranged with the President, Vice President, Marketing Manager, the Chief Engineer and another Engineering Manager at the Case Firm1. At this company, both the President and Vice President have engineering responsibilities with new products. Interviews were also arranged with the President and Marketing Manager of Case Firm2. Each interview took 2-3 hours. In the semi-structured interview not all the questions were asked of each individual. An overlap in questions was used in order to look for any discrepancies or unusual practices within the NPD program that might need further clarification.

For systems dynamics modeling, it is important to focus on how the process changes over time. In order to look at the dynamic relationships, 'graphic modeling' exercises[1] were conducted to focus on the important relationships within the model proposed in the dissertation. Approximately 1-2 hours were spent on the interview questions and 0.5-1.0 hours were spent on the modeling exercises.

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[1] David Lounsbury, a student of Dr. Levine, was kind enough to share his 'graphical modeling' exercises.

Interview Procedures:

- Each interview started by explaining the Human Subjects in Research policy and obtaining the signature of interviewee indicating that the interview process is being recorded and may be stopped at any point upon request of the interviewee. A copy of the signed form was given to the interviewee in the event they wished to contact UCIRHS at a later date.

- The discussion was started by briefly describing the primary interests of this study is to look at the new product development process of the firm. The goal of the first part of the interview was to look at the overall new product process. The second half of the interview put more emphasis on the adoption of new technologies as it pertains to systems dynamic modeling, which looks at how the relationship between factors important to the model change over time.

- An effort was made to keep the interview conversational in order to listen to the "story" the interviewee had regarding their involvement in new product development. It was important to capture both successful adoption events as well as failed adoption events and how the NPD process was affected by the introduction of these new technologies.

- If time did not allow for both the semi-structured interview and the systems dynamics exercises, the worksheets were left with the respondent and returned at a later date or another interview time can be scheduled. Again, not all questions of either Part 1 or Part 2 were asked of all respondents.

Part 1: Semi-structured Interview Questions

- After the lead in and the 1st question, the interview did not follow any particular schedule. An attempt was made to focus on as many of the questions within this list in the allotted time, but in no particular order. The flow of the conversation was dictate in whatever sequence the questions were asked. Additional questions not listed here may have been added if necessary. The list of questions asked were:

1. Where do ideas come from regarding new products? Can you give me an example?

2. Describe a new technology brought in-house within the last year to help build new products which you consider a success. How did it help to build a new product? Can you describe the process?

3. Can you describe the development process this product took? For example, tell me what happened after this idea was presented to the company? What happened next?

4. Was this a completely new product idea for the company or a revision of an existing one?

5. Who was involved in bringing this technology in house? What role did they play?

6. How did it change the way you did things? Changes in the engineering department? Changes in marketing? Changes in manufacturing? How did its importance change over time?

7. What did it allow you to do differently that you may not have been about to do previously?

8. What is your definition of the successful *adoption* of an a new technology into the firm? (Assimilation, Implementation, Efficacy)?

9. What problems did you encounter in using this new technology?

10. What are the biggest challenges you face when building new products? How has this changed over the last year? Last five years? Is this cyclical?

11. What different types of challenges do you experience from a totally new product idea compared to an incrementally new product idea?

12. You described a new technology which resulted in a successful (failed) new product. Could you please describe a new technology brought in house that did not (did) lead to a successful new product?

13. You described two technologies that were brought in house, one lead to a successful new product and one did not.. What criteria requirements do you have for new technologies? Definitive project use? Budget constraint? Personnel constraint?

14. How do you define success (failure) of a *new product*?

15. Could you draw me a flow chart or time line of the typical NPD process in your organization?

16. In this flow chart, I see you have (not) included reference to marketing involvement. When does marketing get involved in the new product development process? [H3]

17. When does marketing get involved with product development? How often do team members interact? Does this change over time?

18. When would marketing get involved in determining which new technologies are adopted by the firm?

19. How does involving marketing impact how a new technology is used in house?

20. Does this change based on the success or failure of a new product Deleted? Can you provide an example? (un-modeled path NPD program success → R&D/MKTG Integration).

21. How does this change with failed new products? Can you give me an example?

22. How do engineers monitor technological changes in your industry? trade shows? publications? customers? suppliers [Adaptive Capacity]

23. How do the engineers keep current with new technology? attend seminars? obtain degrees? etc. [Adaptive Capacity]

24. How do these activities (trade shows, etc.) impact new product development activities?

25. What % of your existing product line is protected by patents? How many new products have you introduced in the last year that are protected by patents? [Adaptive Capacity]

26. How does marketing monitor the market place? trade shows? marketing research activities, etc. [Adaptive Capacity]

27. How does marketing keep current with new marketing ideas? seminars? other education? [Adaptive Capacity]

28. How do these marketing activities (trade shows, etc.) impact new product development activities?

29. Has there been a recent year where the firm was very successful in introducing new products? (not all products – just new products)

30. Why was this a successful year? How did the success impact the firm? Did you in/decrease R&D activities & spending? in/de marketing activities & spending? [h11]

31. Did this success lead to a more structured or more flexible organization?

32. Can you recall a recent year where you did not introduce many new products? How did this less than successful year impact the firm?

33. How did it affect R&D activities and spending? Marketing activities & spending? Was anyone let go? Were any experts or other specialists hired? Were any perks taken away? Did conference attendance in/decrease?

34. What effects did the failure have on the NPD process? More rigid requirements? More flexibility to explore new technologies? [H10]

35. Has there been a time you missed a market opportunity for a new product? What happened? Has anything been done to avoid this situation in the future?

36. How are resources assigned to new technology decisions. Are there constraints on how much is allocated? Who makes the decisions on what new technologies get funding or resources?

37. How does this change over the life of a product - from when the idea is first conceived until it is taken out of the market?

38. How much time does the firm spend in R&D on improving existing technologies? How much time is spent on evaluating new technologies for future use?

39. What determines how many new products are undertaken yearly?

40. How does your firm respond to new competitive offerings, price changes, or new technology? How long does it take the firm to react?

41. What determines when you bring a new technology in house? Typically how long is a technology used within the company?

42. What happens when your company has too many projects? What caused this situation? [H4]

43. Did this effect the R&D activities in any way? [H5]

44. How about the marketing activities? [H6]

45. What role do specialists or product champions play in ensuring the success of a new technology introduced into your company?

46. What are the most important internal organization issues that contribute to the success of new products in your organization?

47. How would you describe your firms NP program success compared to your competitors.

48. Are there other companies that you might share R&D information or new technology ideas with but do not necessarily result in new products? Would you please list those companies. Are these old relationship or a new relationships?

Part 2 : Systems Dynamics Modeling

Part two of the interviews introduced the idea of nonlinear relationship in different behaviors of the NP process. The following workbook was shared with the respondent. They were asked to draw in the relationships as they experienced them in the workplace. The drawings were usually accompanied by discussion as the respondent frequently had questions about how to complete this workbook.

When a relationship did not make sense or was not relevant to the respondent, it was skipped.

I. Relationships in the NP Process

Depicting the reference mode of a variable for a given time horizon is considered essential to the development of all system dynamics model-building (Sterman, 2000). The reference mode for most dynamic variables can be depicted using a relatively small number of distinct patterns of behavior. The most common modes of dynamic behavior are shown below.

Figure A.1 Common modes of Linear Behavior over Time

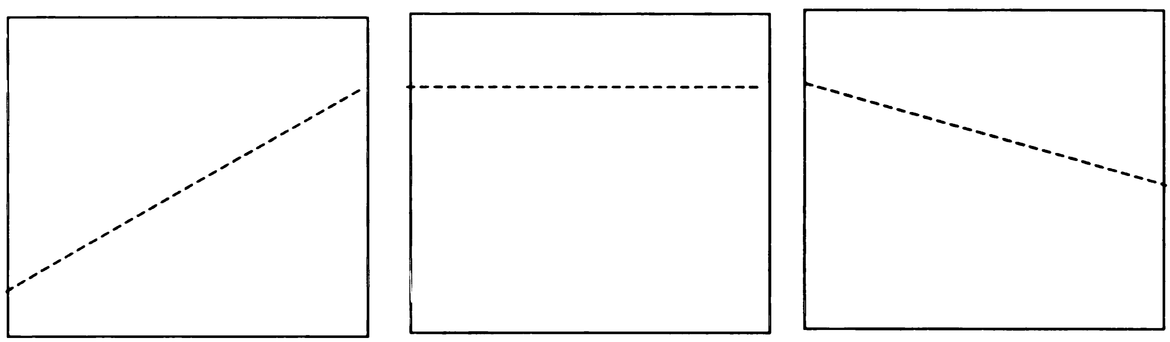
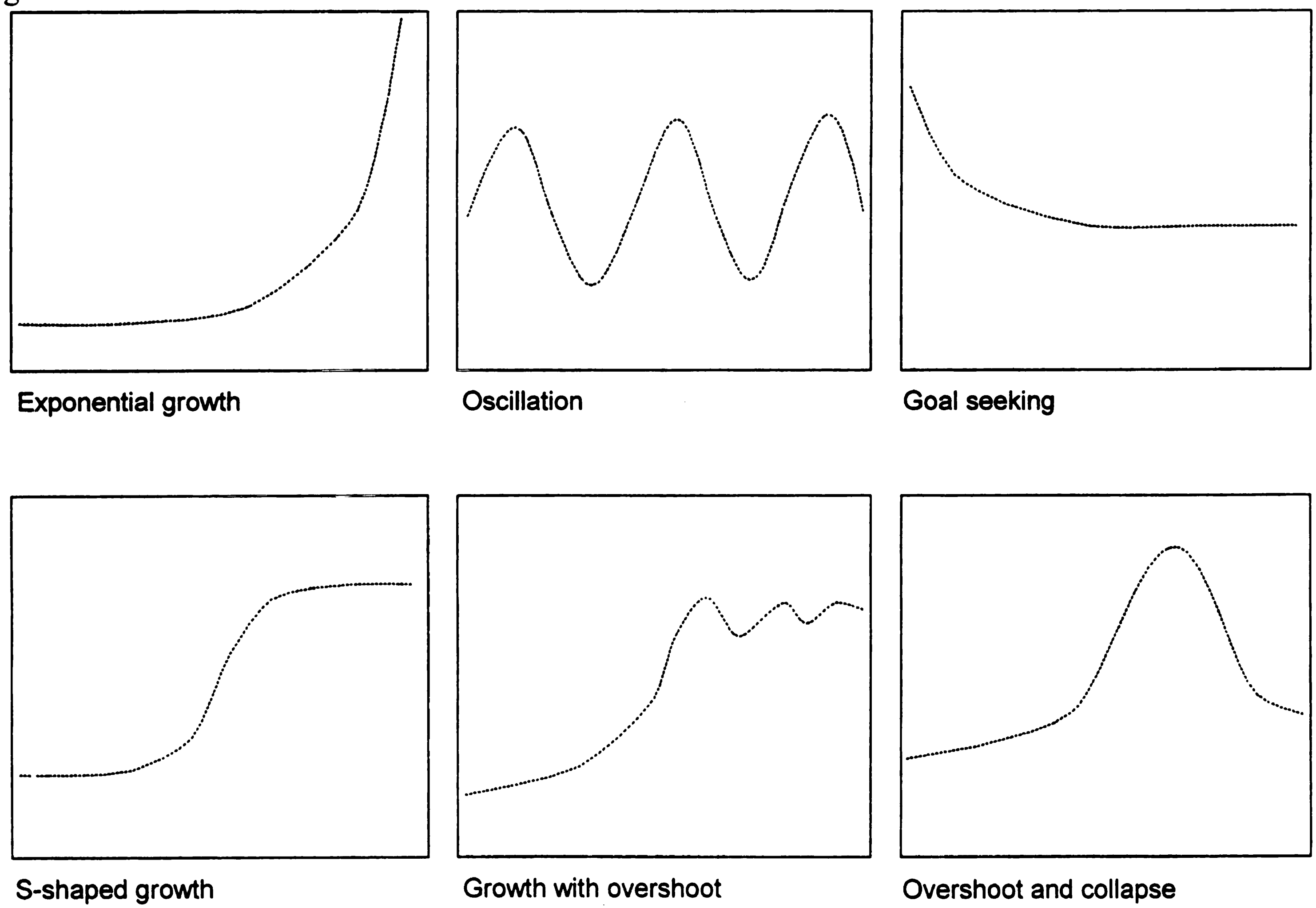


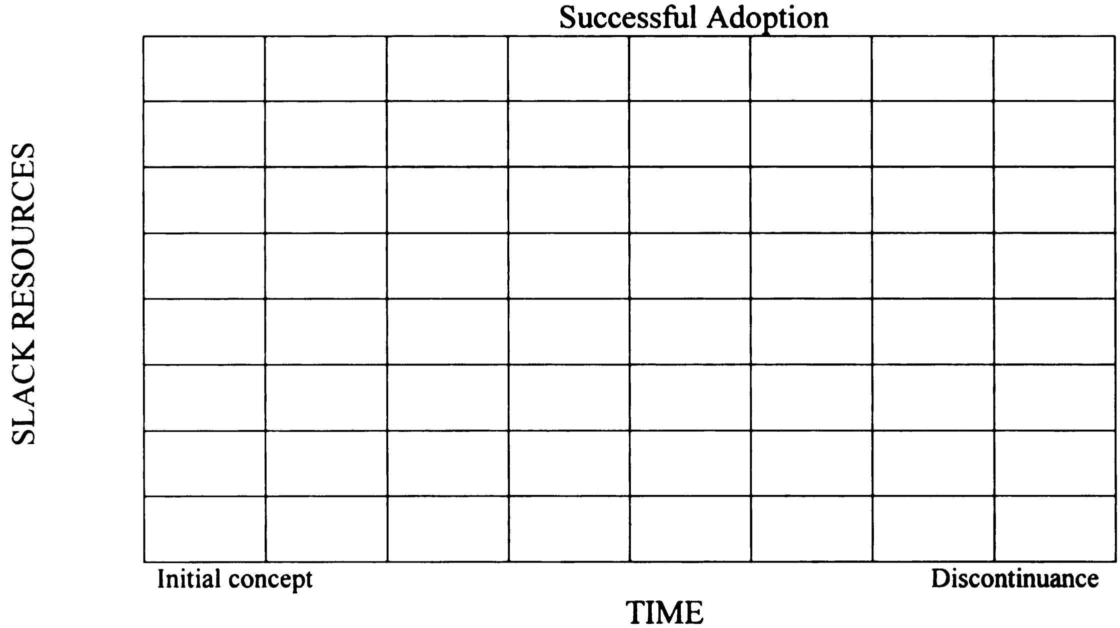
Figure A.2 Common Modes of Curvilinear Behavior over Time



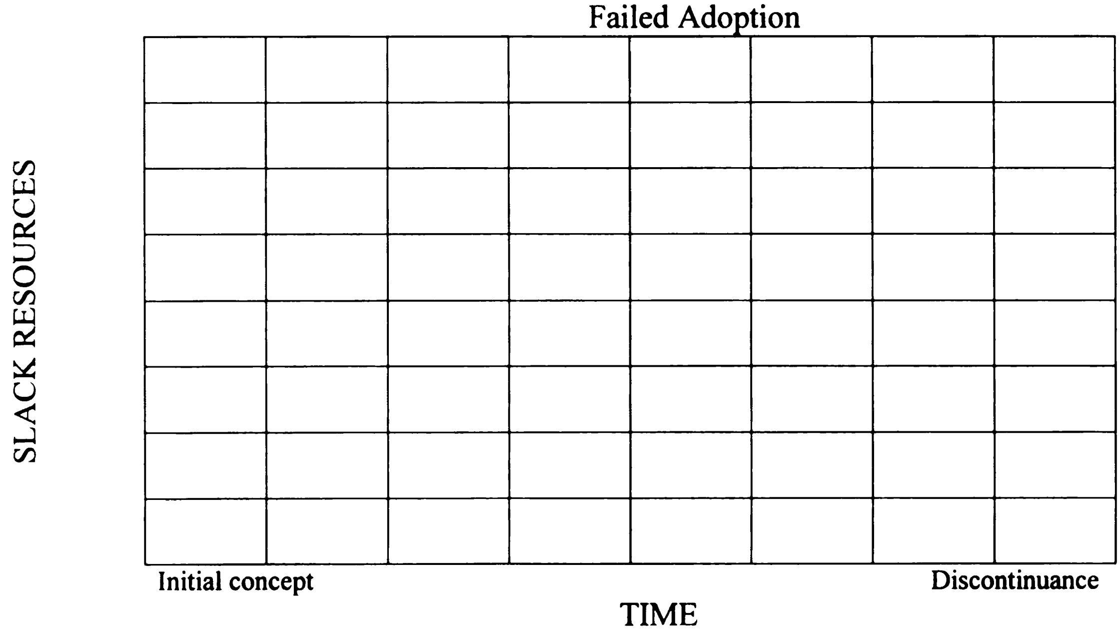
VISUALIZE Slack Resources

Consider Slack Resources made available for the adoption of new technologies. Sketch a reference mode that you believe best describes its shape over the specified time horizon in the real world. Refer to the Figures A1 & A2 (common modes of behavior) for possible ways of sketching the reference mode. Keep in mind that these modes of behavior may be combined with each other. Why do you believe the reference mode for Slack Resources is shaped this way?

Successful Adoption



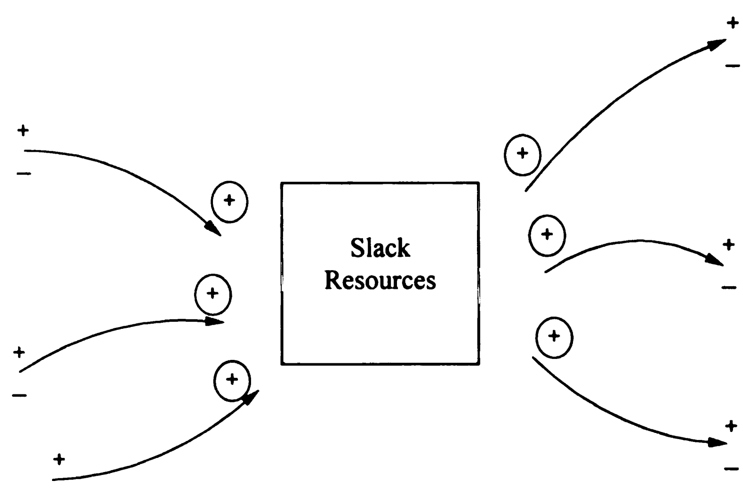
Failed Adoption



Now, using the diagram template below, write in the names of variables that you believe impact Slack Resources <u>over time</u> and that – in turn – Slack Resources impacts <u>over time</u>.

Indicate how you believe these variables are associated with a postive change in Slack Resources. Circle (+) if a positive change in a variable you identified would be expected to cause a positive change in Slack Resources. Circle (-) if a negative change in a variable you identified would be expected to cause a positive change in Slack Resources.

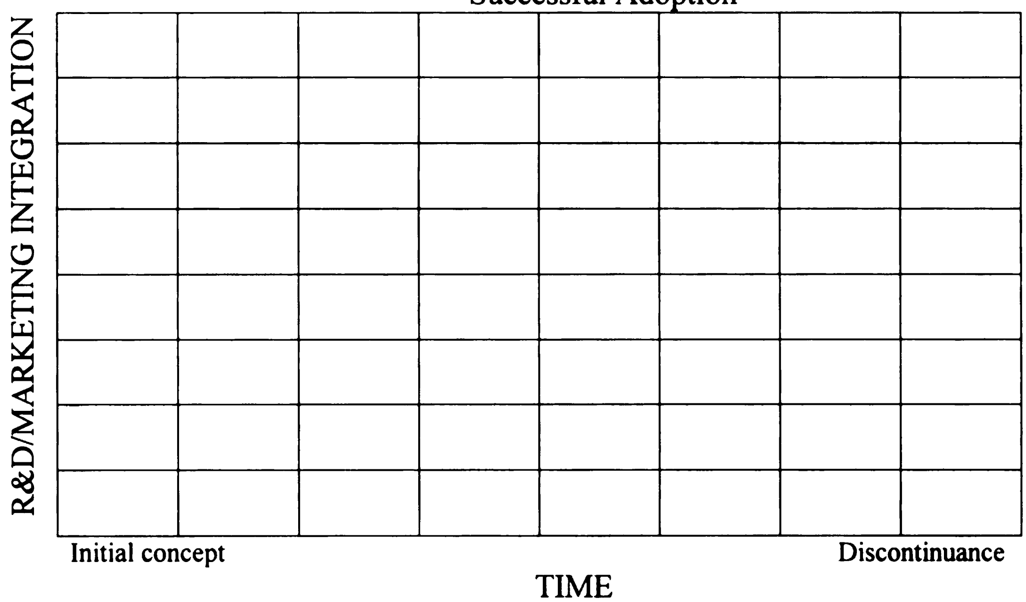
Note that phrases such as 'an increase in,' 'growth of,' 'reinforcement of,' 'higher,' or 'intensification of' can be substituted for 'a positive change in' and that phrases such as 'a decrease in,' 'depletion of, 'dampening of,' 'lower,' or 'weakening of' can be substituted for 'a negative change in.'



VISUALIZE R&D-Marketing Integration

Consider the dynamics of R&D-Marketing Integration for the adoption of new technologies. Sketch a reference mode that you believe best describes its shape over the specified time horizon in the real world. Refer to the Figures A.1 & A.2 (common modes of behavior) for possible ways of sketching the reference mode. Keep in mind that these modes of behavior may be combined with each other. Why do you believe the reference mode for R&D-Marketing Integration is shaped this way?

Successful Adoption



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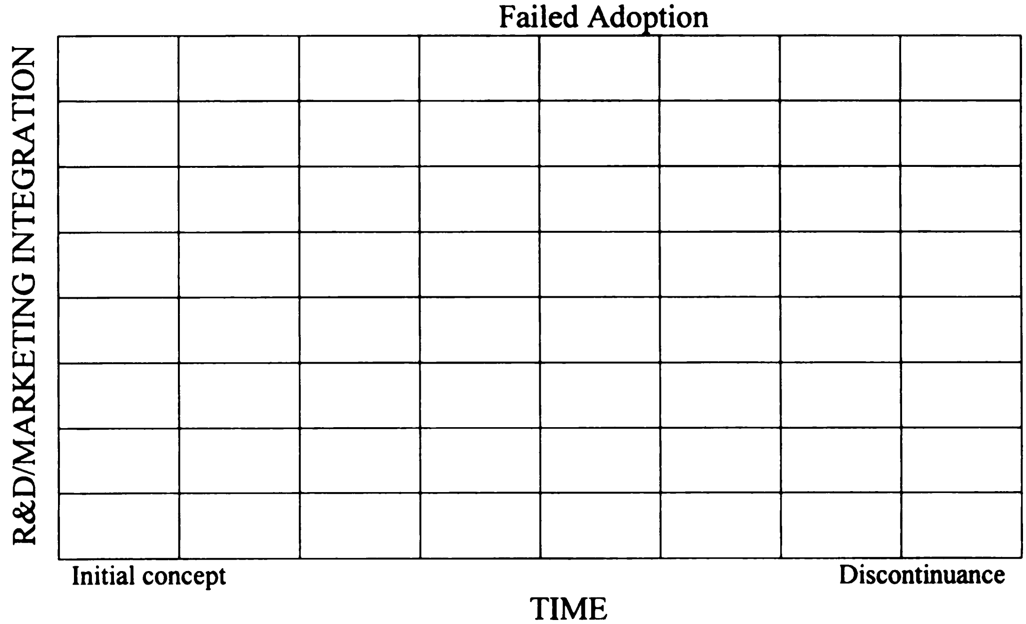
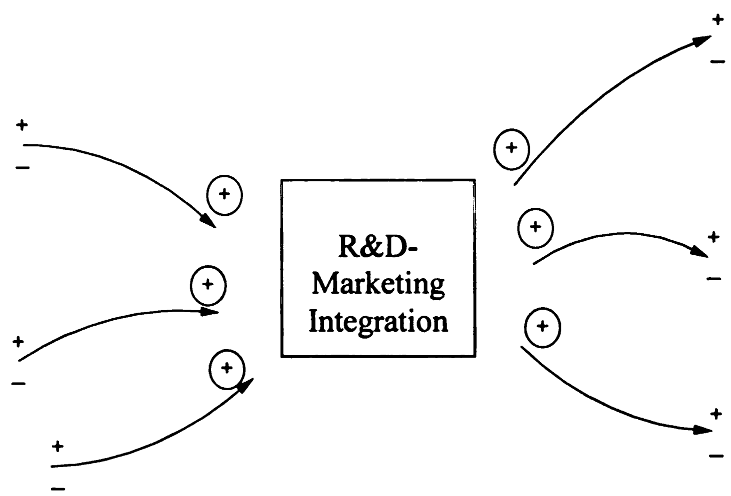


Now, using the diagram template below, write in the names of variables that you believe impact R&D-Marketing Integration over time and that – in turn – R&D-Marketing Integration impacts over time.

Indicate how you believe these variables are associated with a postive change in R&D-Marketing Integration. Circle (+) if a positive change in a variable you identified would be expected to cause a positive change in R&D-Marketing Integration. Circle (-) if a negative change in a variable you identified would be expected to cause a positive change in R&D-Marketing Integration.

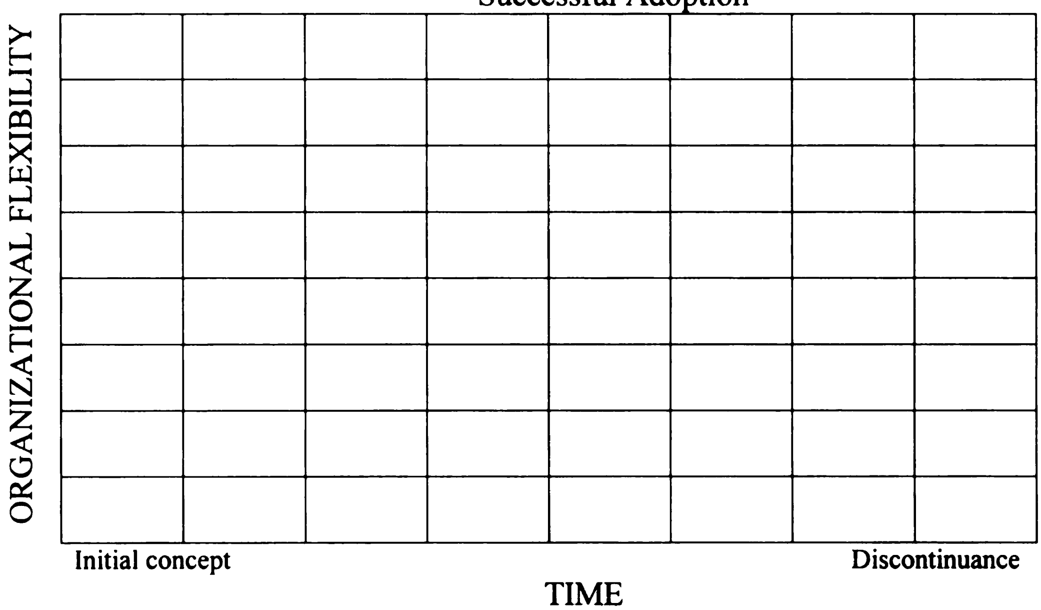
Note that phrases such as 'an increase in,' 'growth of,' 'reinforcement of,' 'higher,' or 'intensification of' can be substituted for 'a positive change in' and that phrases such as 'a decrease in,' 'depletion of, 'dampening of,' 'lower,' or 'weakening of' can be substituted for 'a negative change in.'



VISUALIZE Organizational Flexibility (Adaptive Capacity)

Consider the dynamics of Organizational Flexibility for the adoption of new technologies. Sketch a reference mode that you believe best describes its shape over the specified time horizon in the real world. Refer to the Figures A.1 & A.2 (common modes of behavior) for possible ways of sketching the reference mode. Keep in mind that these modes of behavior may be combined with each other. Why do you believe the reference mode for Organizational Flexibility is shaped this way?

Successful Adoption



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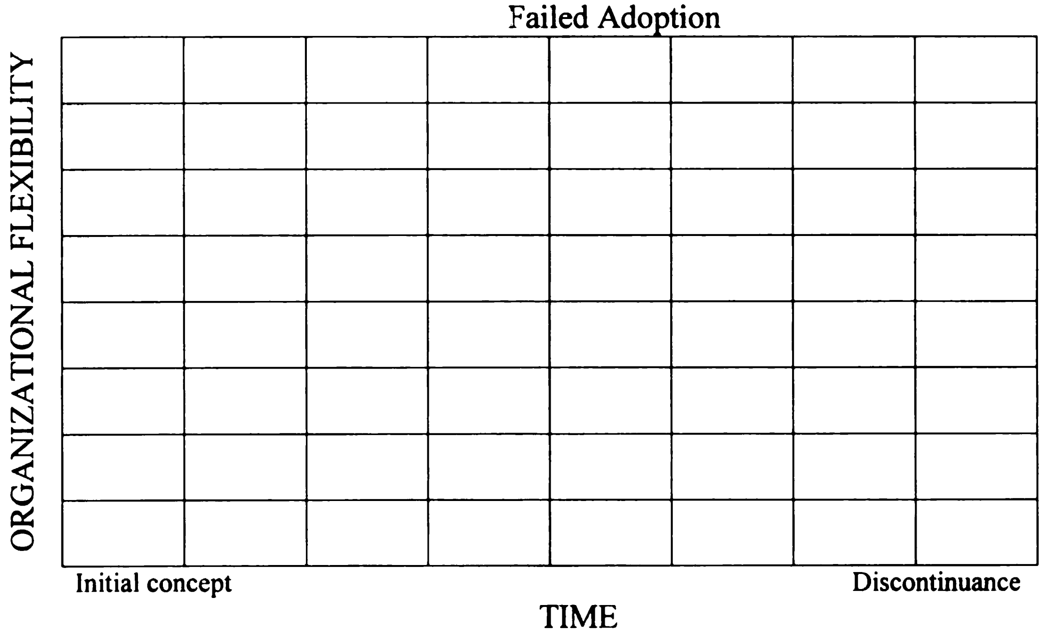
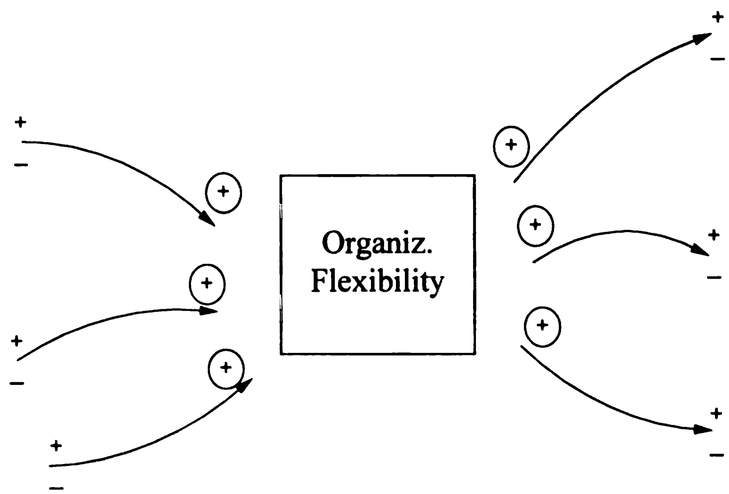


Now, using the diagram template below, write in the names of variables that you believe impact Organizational Flexibility over time and that – in turn – Organizational Flexibility impacts over time.

Indicate how you believe these variables are associated with a postive change in Organizational Flexibility. Circle (+) if a positive change in a variable you identified would be expected to cause a positive change in Organizational Flexibility. Circle (-) if a negative change in a variable you identified would be expected to cause a positive change in Organizational Flexibility.

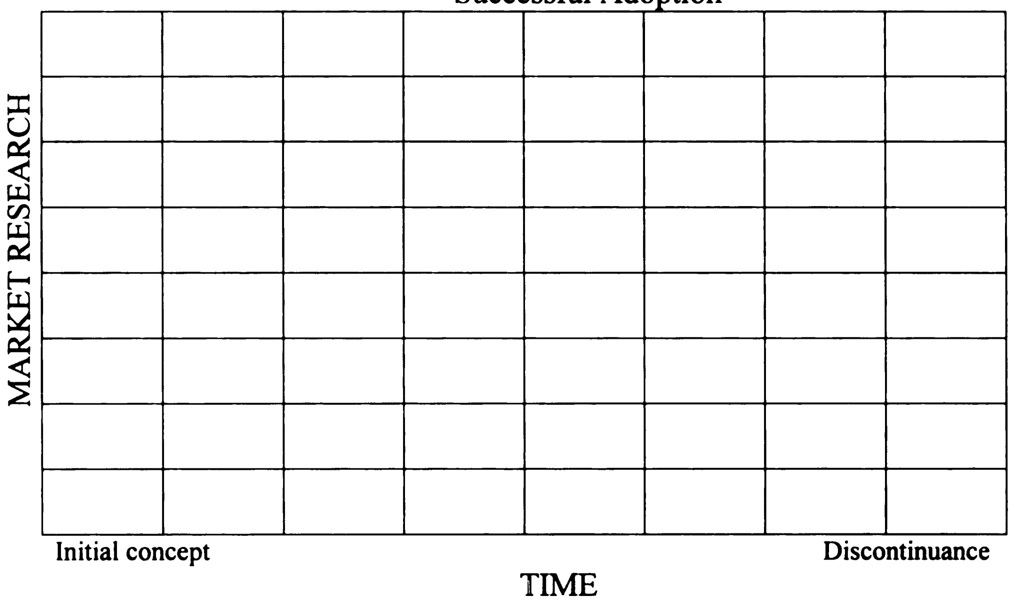
Note that phrases such as 'an increase in,' 'growth of,' 'reinforcement of,' 'higher,' or 'intensification of' can be substituted for 'a positive change in' and that phrases such as 'a decrease in,' 'depletion of, 'dampening of,' 'lower,' or 'weakening of' can be substituted for 'a negative change in.'



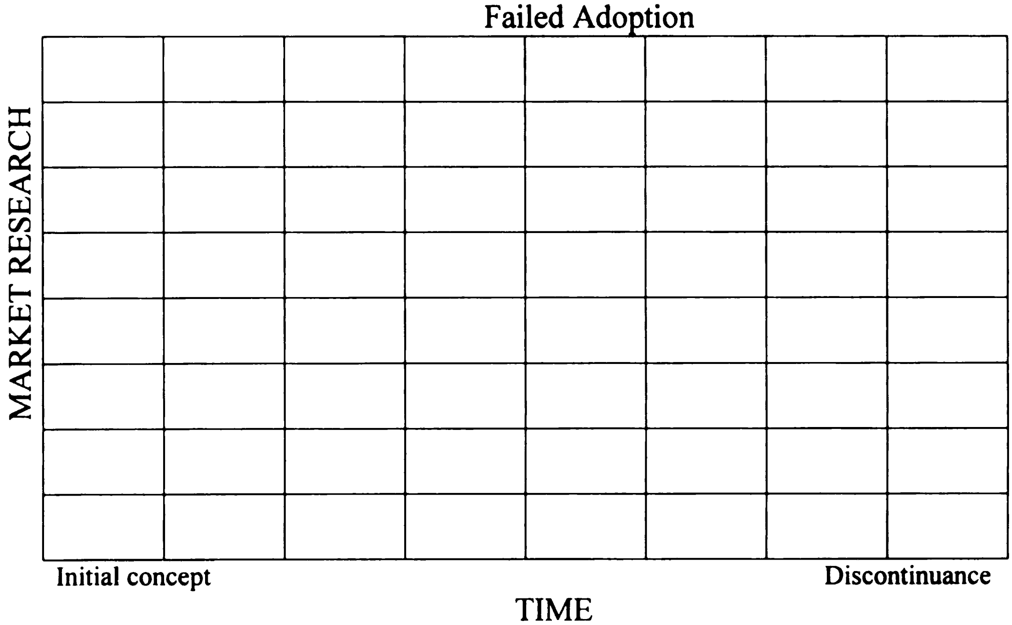
VISUALIZE Market Proficiencies

Consider the dynamics of Market Research Activities for the development of new innovations. Sketch a reference mode that you believe best describes its shape over the specified time horizon in the real world. Refer to the Figures A.1 & A.2 (common modes of behavior) for possible ways of sketching the reference mode. Keep in mind that these modes of behavior may be combined with each other. Why do you believe the reference mode for Market Research Activities is shaped this way?

Successful Adoption



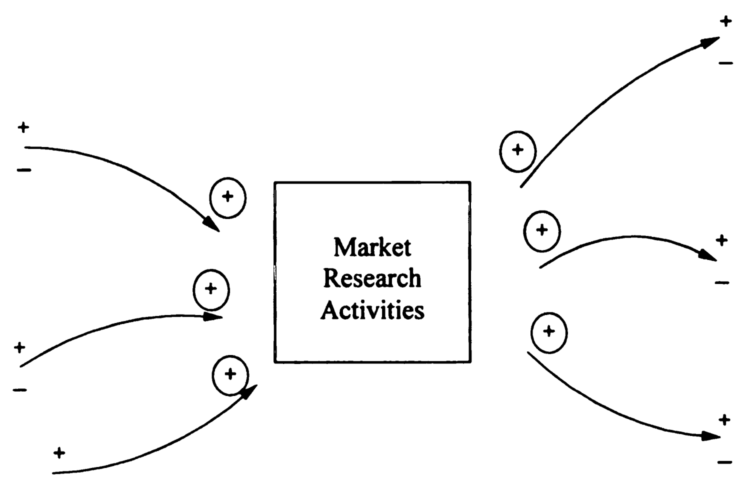
Failed Adoption



Now, using the diagram template below, write in the names of variables that you believe impact Market Research Activities over time and that – in turn – Market Research Activities impacts over time.

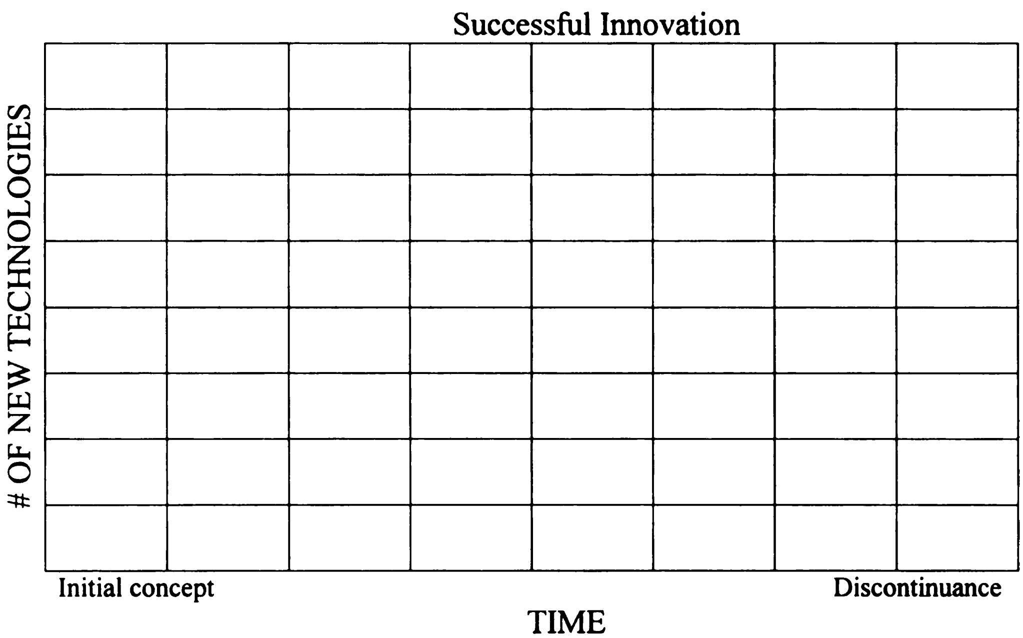
Indicate how you believe these variables are associated with a postive change in Market Research Activities. Circle (+) if a positive change in a variable you identified would be expected to cause a positive change in Market Research Activities. Circle (-) if a negative change in a variable you identified would be expected to cause a positive change in Market Research Activities.

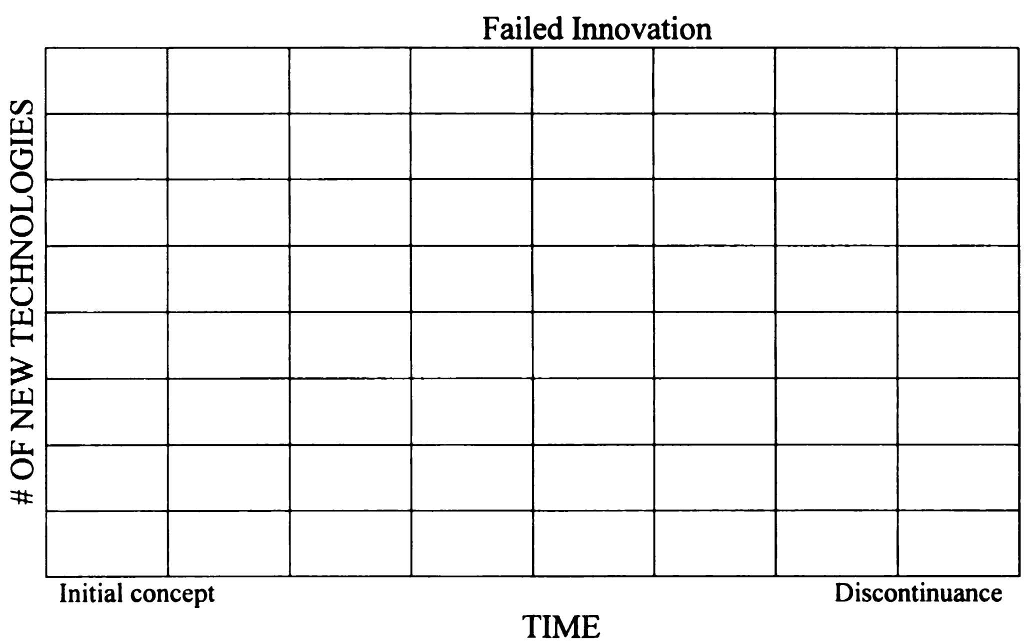
Note that phrases such as 'an increase in,' 'growth of,' 'reinforcement of,' 'higher,' or 'intensification of' can be substituted for 'a positive change in' and that phrases such as 'a decrease in,' 'depletion of, 'dampening of,' 'lower,' or 'weakening of' can be substituted for 'a negative change in.'



VISUALIZE Number of New Technologies Adopted

Consider the dynamics of Number of New Technologies Adopted with the development of new innovations. Sketch a reference mode that you believe best describes its shape over the specified time horizon in the real world. Refer to the Figures A.1 & A.2 (common modes of behavior) for possible ways of sketching the reference mode. Keep in mind that these modes of behavior may be combined with each other. Why do you believe the reference mode for Number of New Technologies Adopted is shaped this way?

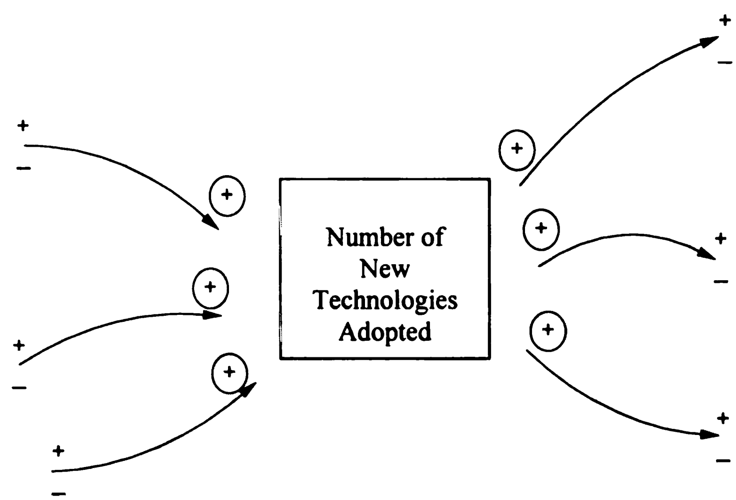




Now, using the diagram template below, write in the names of variables that you believe impact Number of New Technologies Adopted over time and that – in turn – Number of New Technologies Adopted impacts over time.

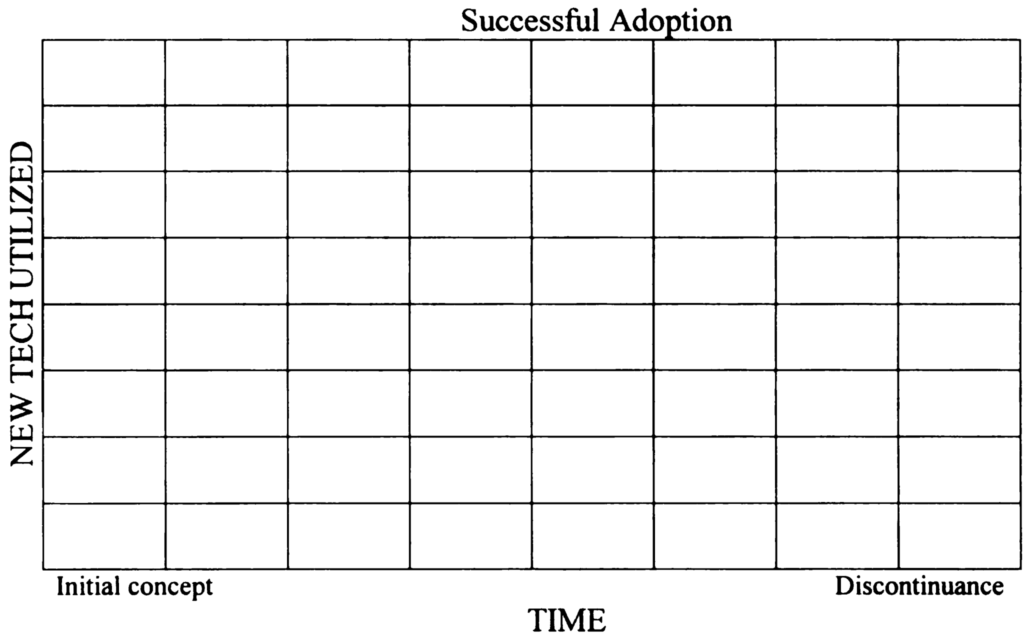
Indicate how you believe these variables are associated with a postive change in Number of New Technologies Adopted. Circle (+) if a positive change in a variable you identified would be expected to cause a positive change in Number of New Technologies Adopted. Circle (-) if a negative change in a variable you identified would be expected to cause a positive change in Number of New Technologies Adopted.

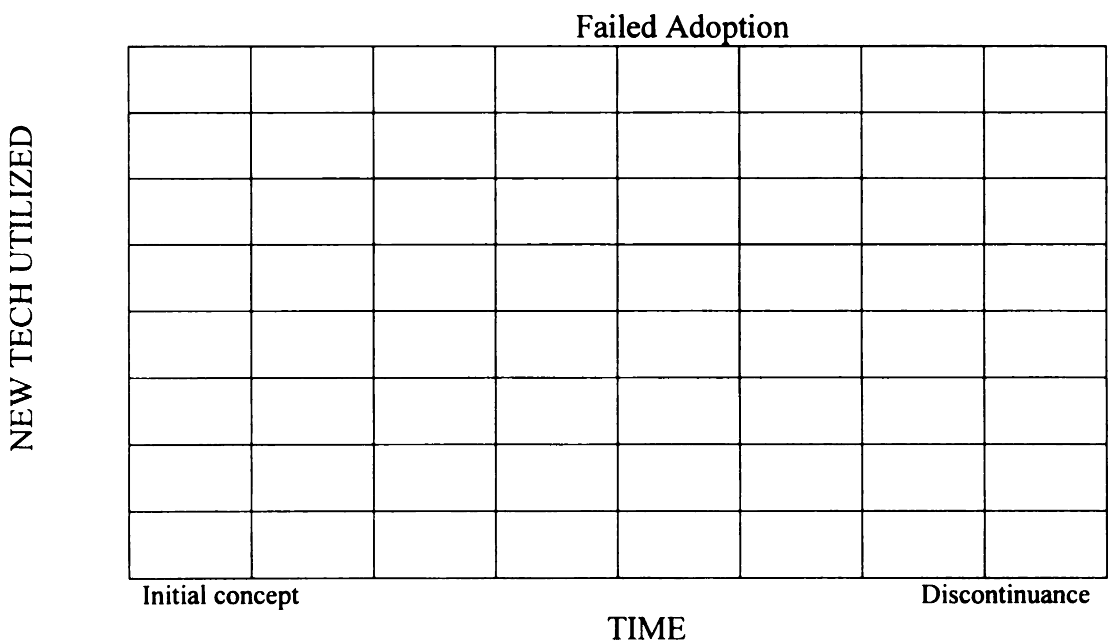
Note that phrases such as 'an increase in,' 'growth of,' 'reinforcement of,' 'higher,' or 'intensification of' can be substituted for 'a positive change in' and that phrases such as 'a decrease in,' 'depletion of, 'dampening of,' 'lower,' or 'weakening of' can be substituted for 'a negative change in.'



VISUALIZE New Technology Utilization

Consider the dynamics of New Technology Utilization with the development of new innovations. Sketch a reference mode that you believe best describes its shape over the specified time horizon in the real world. Refer to the Figures A.1 & A.2 (common modes of behavior) for possible ways of sketching the reference mode. Keep in mind that these modes of behavior may be combined with each other. Why do you believe the reference mode for New Technology Utilization is shaped this way?

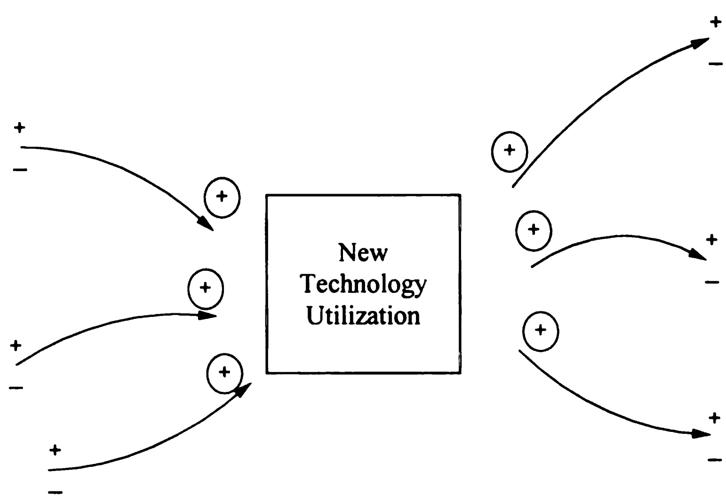




Now, using the diagram template below, write in the names of variables that you believe impact New Technology Utilization over time and that – in turn – New Technology Utilization impacts over time.

Indicate how you believe these variables are associated with a postive change in New Technology Utilization. Circle (+) if a positive change in a variable you identified would be expected to cause a positive change in New Technology Utilization. Circle (-) if a negative change in a variable you identified would be expected to cause a positive change in New Technology Utilization.

Note that phrases such as 'an increase in,' 'growth of,' 'reinforcement of,' 'higher,' or 'intensification of' can be substituted for 'a positive change in' and that phrases such as 'a decrease in,' 'depletion of, 'dampening of,' 'lower,' or 'weakening of' can be substituted for 'a negative change in.'



APPENDIX B

System Dynamics Modeling Supporting Documents

Appendix B Contents

Table B.1 Parameters (Constants) used in Vensim Modeling

Symbol	Label	Definition	Constants
C_{AC}	unit conversion	1 unit in performance gap becomes 0.10 units of adaptive capacity	.10 performance/ adaptive cap
C_D	exploit resources / projects	resources required for 1 development project	1 resource/projec t
C_E	quarterly cost/explore project	quarterly cost of maintaining a exploration project	0.125 expense units
C_I	converter integration/ products	units of Marketing-RD integration from 1 successful exploitation project	1 integration unit
C_K	knowledge/ project constant	knowledge units required for 1 development project	5 knowledge units
C_P	converter performance/ products	units of performance from 1 unit of profits	1 performance
$C_{P\text{-}K}$	proficiencies / knowledge converter	units of Marketing or R&D Proficiency gained from 1 unit of knowledge	.20 proficiency units
$C_{P\text{-}P}$	converter products/ projects	# of products resulting from a development project	2
C_{SR}	perform/slack conversion	# performance gap allocated to slack resources	1
C_R	explore resources/ project	resources required for 1 research project	2.5 resources/ project
f_1	fracdeath1	% of new products at end of PLC quarterly	10%
f_2	fracdeath2	% of products 1-5 years old at end of PLC quarterly	10%
f_3	fracdeath3	% of products 6-10 years old at end of PLC quarterly	25%
f_{AC}	frac decrease in AC	% decrease in Adaptive Capacity per quarter	1%
f_{cat}	frac catalytic	% of exploration projects resulting in catalytic innov	10%

Table B.1 Parameters (con't)

f_D[2]	frac fail	% of development projects failing to reach completion	11%
$f_{launched}$[2]	frac success launch rate1	% of products launched successfully	95%
f_{lose}	frac decrease	% of resources lost quarterly because they are unused	5%
f_{mid}	forgetting factor mid	% of mid knowledge forgotten every quarter	1%
f_M	loss factor marketing	% of Marketing Proficiencies lost every quarter	1%
f_{MRD}	frac decrease integration	% erosion in marketing-R&D integration/quarter	10%
f_{new}	forgetting factor new knowledge	% of new knowledge forgotten every quarter	1%
$f_{out\text{-}D}$	frac outdated exploitation	% of 'shelved' development projects that become outdated	1%
$f_{out\text{-}R}$	frac outdated exploration	% of 'shelved' development projects that become outdated	1%
f_R	frac failed exploration	% of research projects failing to reaching completion	12%
$f_{RD\text{-}prof}$	loss factor R&D	% of R&D Proficiencies lost every quarter	10%
k_C	knowledge – catalytic projects	knowledge increase from a catalytic innovation	7 knowledge units
k_D	knowledge – exploit projects	knowledge increase from development project	1 knowledge units
k_f	knowledge – failed projects	knowledge increase from failed development projects	0.25 knowledge units
k_R	knowledge – explore projects	knowledge increase from research project	2.5 knowledge units
n_T	total approved projects	# of projects/quarter that have received approval and funding	6 + f(slack resources)

[2] Historically, the fraction of failed development projects has been noted anywhere from 20-80% (Cooper, 1993). These companies record a much lower % failed as new products brought into development have designated customers; if a product fail they fail after launch not during the development phase.

Table B.1 Parameters (con't)

R	resources	man-hours, capital, funding for new projects	15 resource units/quarter
τ_1	aging new prod	product aging time new products	4 quarters
τ_2	aging prod1-5	product aging time products 1-5 years old	20 quarters
τ_3	aging prod6-10	product aging time products 6-10 years old	20 quarters
τ_4	aging prod10+	product aging time until obsolescence	32 quarters
τ_D	delay on exploit	time to complete a exploitation project	2 quarters
τ_G	delay for target adjustment	delay time to relay information regarding performance gap	2 quarters
$\tau_{K\text{-}innov}$	aging new to mid	time for new knowledge to become mid knowledge	8 quarters
$\tau_{K\text{-}mid}$	aging mid to old	time for mid knowledge to become old knowledge	12 quarters
$\tau_{K\text{-}old}$	aging old	time for old knowledge to become outdated and obsolete	20 quarters
τ_Q	perception time	delay time in receiving info regarding performance	2 quarters
τ_R	delay time	time to complete a research project	4 quarters
$\tau_{SR\text{-}D}$, $\tau_{SR\text{-}R}$	delay exploit (explore) distribution	time delay for distributing slack resources to exploitation (exploration) projects	2 quarters
Π_1	profitnew/product	relative profit units from 1 new product	1.2
Π_2	profit1-5/product	relative profit units from 1 product 1-5 years old	1.0
Π_3	profit16-10/product	relative profit units from 1 product 1-5 years old	0.80
Π_4	profit10+/product	relative profit units from 1 product 1-5 years old	0.75

Table B.2 Stock (Levels) with Initial Values at t=0

Stock	Definition	**Initial Values – all simulations**
Adaptive Capacity, AC(t)	NP program ability to adapt to environment (moderator)	0
Exploitation Projects Requiring Funding, $N_R(t)$	approved development projects awaiting resources	0
Exploration Projects Requiring Funding, $N_D(t)$	approved research projects awaiting resources	0
Innovative Knowledge, $K_I(t)$	Stock of technology knowledge less than 5 years old	5
Marketing Proficiencies, MP(t)	Level of Marketing Proficiencies maintained	0
Marketing-RD Integration, MRD(t)	Level of Marketing-RD Integration maintained	0
Mid Knowledge, $K_M(t)$	Stock of technology knowledge greater than 5 but less than 10 years old	0
New Product<1	Products < 1 year old	0
Old Knowledge, $K_O(t)$	Stock of knowledge greater than 10 years old	0
Perceived Performance: Actual, $P^P(t)$	Actual performance as perceived by management	14
Performance Goal: Target, TP(t)	Target performance	14
Products Launched, $P_{launch}(t)$	New products launched into the marketplace	0
Products1-5yr, $P_{1\text{-}5yr}(t)$	Products 1-5 years old	10
Products6-10yr, $P_{6\text{-}10yr}(t)$	Products 6-10 years old	10
Products10+, $P_{10yr}(t)$	Products 10+ years old	5
Quarter Profits, Q(t)	Profits from products	14
R&D Proficiencies, RDP(t)	R&D proficiencies for NPD activities	10

Table B.2 Stock (Levels) with Initial Values at t=0 (con't)

Resources for Exploration, $R_R(t)$	Resources allocated to exploration projects	0
Resources for Exploitation, $R_D(t)$	Resources allocated to exploitation projects	0
Slack Resources, SR(t)	Slack resources available for projects	0
Technology Exploration, $E_R(t)$	# or ongoing exploration projects/quarter	0
Technology Exploitation, $E_R(t)$	# or ongoing exploitation projects/quarter	0

Table B.3 Auxiliary Variables used in Vensim Modeling

Label	Definition
AC moderating effects	Adaptive Capacity acts as a amplifier (moderator) to marketing and R&D proficiencies
Catalytic Innovations, P_C	number of catalytic innovations per quarter that result from exploration (research) projects
discount factor AC Old-Know	amplifier effect of adaptive capacity; when adaptive capacity < 0 then Old and Mid knowledge is not discounted, but New Knowledge is.
discount factor AC Mid-Know	amplifier effect of adaptive capacity; when adaptive capacity = 0 then Mid knowledge is not discounted, but Old and New Knowledge are.
discount factor AC I-Know	amplifier effect of adaptive capacity; when adaptive capacity > 0 then New knowledge is not discounted but old and Mid knowledge are.
exploration project constraint	constraint on new projects; can only undertake new projects if (1) resources are available, and (2) projects have been approved
exploitation project constraint	constraint on new projects; can only undertake new projects if (1) resources are available, and (2) projects have been approved

Table B.3 (con't) Auxiliary Variables

Label	Definition
expenses	quarterly expenses incurred by maintaining exploration projects
frac slack resources to exploration	fraction of slack resources allocated to exploration projects
fraction resource allocation to exploration, $f_{R/D}$	fraction of resources allocated to exploration projects; 1- $f_{R/D}$ goes to exploitation (development) projects
GAP: (Target – Actual), G_t	gap in performance where the target exceeds the actual
knowledge limitation	constraint on new projects; can only undertake new projects if the knowledge stock is available
marketing-R&D constraint	constraint on timing of new projects; if marketing-R&D stock goes below 0, then projects are delayed by 2 quarters
Mktg constraint	constraint on success in launch of new products, if marketing proficiencies < 0, then decrease success factor by 2
profitnew	profits from product less than 1 year old
profit1-5	profits from product 1-5 years old
profit6-10	profits from product 6-10 years old
profit10+	profits from product 10+years old
perception gap	gap between actual performance and perceived performance due to time delays or other 'misperceptions'
quarterly slack	constraint on quarterly slack; only when the actual exceed the target does slack resources become available
R&D constraint	constraint on success in launch of new products, if R&D proficiencies < 0, then decrease success factor by 2
total approved projects	quarterly total number of approved projects (both research & development)

B.1 Differential Equations used in SD Model

B.1.1 Resources Equations

Resources are identified as "slack" resources and "budgeted" resources. Slack resources, $SR(t)$, is defined as a function of the performance gap, $G(t)$, in the overall program. The gap is defined as *target performance – actual performance* (see section B.1.7.1 below). Slack resources only become available when the gap is less than zero $G(t) < 0$, or actual performance exceeds target performance. The inflow to slack resources, sr_{in}, is defined as follows:

$$sr_{in} = \alpha_{SR} G(t)\text{; } \alpha_{SR} = 0 \text{ when } G(t) \geq 0 \text{ and } \alpha_{SR} = c_{SR} \text{ when } G(t) < 0 \qquad \text{(B.1)}$$

where c_{SR} represents the percentage of the total slack resources invested back into the NPD program. Outflow of slack resources models the allocation of slack resources to projects:

$$sr_{out\text{-}exploitation} = \frac{(1 - f_{R/D})SR(t)}{\tau_{SR-D}} \qquad \text{(B.2)}$$

$$sr_{out\text{-}exploration} = \frac{f_{R/D}SR(t)}{\tau_{SR-R}} \qquad \text{(B.3)}$$

where the fraction of exploration projects to exploitation projects approved, $f_{R/D}$, is a function of the performance gap as well and τ_{SR-D} and τ_{SR-R} is the time delay in allocating resources.

"Budgeted" resources are defined as resources allocated to the new product program under standard operating policies. The amount is typically budgeted annually by upper management. These standard resources are allocated to exploration and exploitation as $r_R = (f_{R/D})R_R$ and $r_D = (1 - f_{R/D})R_D$. This implies that every quarter, managers make decisions on how to allocate resources based on the past quarter's performance level. The stocks, *Resources to Exploration* and *Resources to Exploitation* are represented as;

$$R_R = \int \frac{ds r_{\text{out-explore}}}{dt} + \frac{dr_{\text{explore}}}{dt} - \left(\frac{dr_{\text{lost-explore}}}{dt} + \frac{dr_{\text{allocated-explore}}}{dt} \right) + R_R(0) \quad \text{(B.4)}$$

$$R_D = \int \frac{ds r_{\text{out-exploit}}}{dt} + \frac{dr_{\text{exploit}}}{dt} - \left(\frac{dr_{\text{lost-exploit}}}{dt} + \frac{dr_{\text{allocated-exploit}}}{dt} \right) + R_D(0) \quad \text{(B.5)}$$

$\frac{dr_{\text{lost}}}{dt}$ represents resources "lost" if not used within the quarter. This policy of "don't use-lose" is standard practice in many organizations. Unused resources indicate too generous of a budget that may better be used in other functional areas of the organization.

B.1.2 Exploration and Exploitation Equations

At each quarter, the NPD program undertakes n_T new projects, which is a function of the resources available such that;

$$n_T = \frac{R_c + SR(t)}{c_R} \quad \text{(B.6)}$$

where c_R is the maximum resources that might be required for a research project. Since R_c (quarterly standard resources) is typically constant, the variability in the number of projects undertaken in a quarter is a function of the availability of slack resources. $N_R(t)$, the number of approved research projects, and $N_D(t)$, the number of approved development projects for the quarter. Each is determined by $N_R(t) = f_{R/D}(n_T)$ and $N_D(t) = f_{R/D}(1 - n_T)$.

Two stocks, *Exploration Projects Requiring Funding, $N_R(t)$,* and *Exploitation Projects Requiring Funding, $N_D(t)$* represent projects that have received "approval" but have not received funding. These stocks act as a "limiter" which insures that only projects that have funding are actually undertaken. Additionally it allows projects to be "shelved" until funding becomes available. Projects that aren't funded can become outdated after a set time, $\tau_{outdate}$. Projects that do receive funding, $\frac{drp_{in}}{dt}$ and $\frac{ddp_{in}}{dt}$ become the inflows for the stocks, *Technology Exploration* and *Technology Exploitation.*

$$\frac{dE_{\text{R-in}}}{dt} = Min(R(t)/c_R, N_R(t)) \tag{B.7}$$

$$\frac{dE_{\text{D-in}}}{dt} = Min(R(t)/c_D, N_D(t), KS_T(t)/c_K) \tag{B.8}$$

where c_R and c_D are constants that determine resources required to undertake an exploration (research) projects or exploitation project (development), respectively. $KS_T(t)$ represent the total knowledge stock at time = t, and $KS_T(t)/c_K$ represents the knowledge stock required to undertake a new development project. Exploration projects can only be added to the exploration stock, E_R, if there are adequate resources available. Likewise, exploitation projects can only be added to the exploitation stock, E_D, if there are adequate resources and sufficient knowledge to undertake a new development project.

Only a fraction of projects undertaken are successful; f_R = fractional success rate of research projects, f_D = fractional success rate of development projects. The number of successful projects is represented by $f_R E_R(t)/\tau_R$ and $f_D E_D(t)/\tau_D$ where τ_R and τ_D are the average time to complete a project. Unsuccessful projects are represented by $(1-f_R)E_R(t)$ and $(1-f_D)E_D(t)$. In this study, $\tau_R = 4$ quarters and $\tau_D = 2$ quarters.

B.1.2.1 Catalytic Innovations

A percentage of the successful research projects are catalytic innovation, the focus of this study. Catalytic innovations are modeled as

$$P_C = f_{cat}(f_{RD}E_R(t)) \tag{B.9}$$

Catalytic innovations, as previously discussed, are innovations discovered during research activities that act as a catalyst to instigate new research projects and new product development projects not originally planned by the firm. Catalytic innovations also embody new knowledge that is more valuable to the organization compared to the standard results from research activities. In this study $f_{cat} = 0.10$, based on the fact that 10% of inventions are considered new-to-the-world innovations (Griffin, 1997).

B.1.3 Technology Knowledge Equations

Each successful project results in "learning" or a gain in knowledge. The amount of knowledge gained (inflow) from a project is variant. Catalytic projects have higher means and variances in knowledge acquisition compared to research projects, where $\mu_C > \mu_R > \mu_D$ and $\sigma_C^2 > \sigma_R^2 > \sigma_D^2$ (March, 1991). New knowledge is also acquired from successful development and failed development projects. These are modeled as constant proportions of these types of projects, or as;

$$K_f = (1-f_D)E_D(t)c_{K_D\text{-fail}} \tag{B.10}$$

$$K_D = f_D E_D(t)c_{K_D\text{-success}} \tag{B.11}$$

where $c_{K_D\text{-fail}} = 0.25$ and $c_{K_D\text{-success}} = 1.0$ in this study.

Total knowledge is modeled as three stocks; *Innovative Knowledge*, *Mid Knowledge* and *Old Knowledge*. *Innovative Knowledge* is new technological knowledge acquired within the past four quarters. Knowledge more than two years old becomes *Mid Knowledge*, and *Old Knowledge* is more than 5 years old. Modeling knowledge as three different stocks is required as not all technological knowledge is treated equally by the organization. The knowledge stocks are modeled as:

$$K_I(t) = \int \frac{dK_R}{dt} + \frac{dK_D}{dt} + \frac{dK_f}{dt} + \frac{dK_C}{dt} - \frac{dK_{I\text{-lost}}}{dt} - \frac{dK_{I-aging}}{dt} + K_I(0) \tag{B.12}$$

$$K_M(t) = \int \frac{dK_{I-aging}}{dt} - \left(\frac{dK_{M-aging}}{dt} + \frac{dK_{M-lost}}{dt} \right) + K_M(0) \tag{B.13}$$

$$K_O(t) = \int \frac{dK_{M-aging}}{dt} - \frac{dK_{O-aging}}{dt} + K_O(0) \tag{B.14}$$

The outflows represent the fractional knowledge lost by the departure of key employees, the shelving of technology for future use, or even new technology replacing old technology.

It is important to note that 'dated' knowledge is not necessarily useless or ineffective. In some cases it may more useful as proven knowledge since new knowledge may still have some application uncertainties. However, keeping in mind Moore's Law (which predicts that the amount of information storable on a silicon chip will roughly double every), aging knowledge may indeed quickly be ineffectual. The greater the percentage of old knowledge, the greater the need exists to restock innovative technological knowledge through exploration activities. Thus, technically oriented organizations must balance the need to "renew" aging knowledge through research activities and "appropriate rents" from proven older knowledge. In order to model this utilization of different ages of knowledge, *Adaptive Capacity* is modeled as a moderator to the three knowledge stocks. This moderator is a modeled as a inverse s-shaped lookup function (see sec B.1.7.2).

B.1.4 Proficiencies Equations

Both *Marketing Proficiencies* and *R&D Proficiencies* are a function of the gains in knowledge. It is also moderated by adaptive capacity. The higher the adaptive capacity the higher the use of marketing and R&D proficiencies in the building of new products.

$$MP_{in} = K_{I_{in}} * c_{P-K} * AC(t) \tag{B.15}$$

$$RDP_{in} = K_{I_{in}} * c_{P-K} * AC(t) \tag{B.16}$$

where c_{P-K} represents the increase in marketing/R&D proficiencies based on one new knowledge unit. c_{P-K} =0.20 in this study based on conversations with NP managers of the case studies firms.

B.1.5 Marketing-R&D Integration Equations

Marketing-R&D integration is a simple linear function of the number of successfully completed exploitation projects the firm has achieved. The assumption is that is the project has been successfully completed and handed off to marketing for launch, there has been some interaction between the two departments.

$$MRD(t) \ = f(\text{successful exploit projects}) * \ c_{MRD} \tag{B.17}$$

where c_{MRD}=0.25 in this study, which indicates that for every successful exploitation project, marketing and R&D will have interacted with each other at 25% of capacity for the two departments. This number would be higher if the firm was more marketing oriented.

B.1.7 Products/Profit Equations

Product Stocks are also modeled as an aging chain. Products enter the aging chain through *Products Launched* stock;

$$P_{launch}(t) = \int \frac{dE_{D-success}}{dt} - \left(\frac{dP_{launch\text{-}success}}{dt} + \frac{dP_{launch\text{-}failure}}{dt} \right) + P_{launch}(0) \qquad \text{(B.18)}$$

Not all products launched are successful so that $\frac{dP_{launch-failure}}{dt} = \frac{P_{launch}(t)}{\tau_{launch-fail}}$ where

$\tau_{launch-fail} = 0.05$. Successfully launched products become *New Products<1*, $P_{newprod}(t)$. Products that are successful in the market place after 1 year enter the stock, *Products1-5yr*, $P_{1\text{-}5yr}(t)$, which then become *Products6-10*, $P_{6\text{-}10yr}(t)$ and then *Products 10+*, $P_{10yr}(t)$. A similar model is applicable for all four of these stocks;

$$P_{1-5yr}(t) = \int \left(\frac{dP_{newprod-success}}{dt} - \frac{dP_{newprod-failure}}{dt} \right) + P_{1-5yr}(0) \qquad \text{(B.19)}$$

The stock of *Quarterly Profits* is increased by the successful launch of new products into the marketplace and sales of existing products. *Quarterly Profits* is represented by $Q(t) = \pi m$,where m = number of products in marketplace and π is a relative profit level. Actual performance cannot be measured instantaneously.

B.1.7 Performance Gap & Adaptive Capacity Equations

B.1.7.1 Performance Gap

The performance gap, G_t, is a function of the target performance and actual performance. As an auxiliary variable changes with each quarter but does not act as an in/outflow to a stock variable, it is represented by a subscripted *t*.

$$G_t = (\textit{Target Performance} - \textit{Actual Performance}) \tag{B.20}$$

Actual performance is determined by quarterly profits realized. A time delay exists from realization of profits to the actual reporting of profits. Thus, allocation decisions are based on perceived performance, $P^P(t)$, or $\frac{Q(t)}{\tau_Q}$, where τ_Q is the time it takes to transfer the information. *Target Performance,* $TP(t)$, is typically set by upper management although it may be influenced by exogenous factors such as competition. In this study, target performance is modeled here as a "floating goal" (Sterman, 2000). If a NPD program performs below expectations, the target goal will be adjusted downward; if performance is above expectation, the target will be adjusted upward. Since changes in target performance cannot be implemented instantaneously after being set by top management, it may take several time periods for new goals to become reality within the NPD program. The performance gap, G_t, is thus represented by:

$$G_t = \frac{TP(t)}{\tau_G} - P^P(t) \tag{B.21}$$

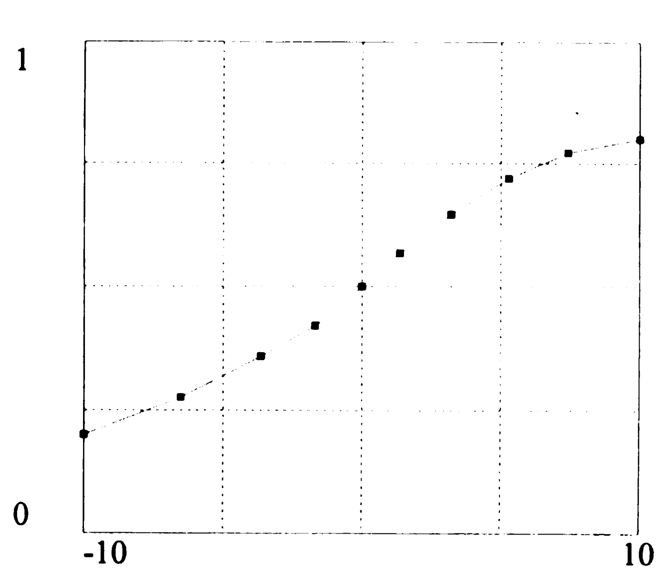
where τ_G is also a time constant to factor in the delay of receiving actual performance information and setting of new target performance goals.

As previously noted in Chapter 4, the fraction of exploration (research) projects compared to exploitation (development) projects approved, $f_{R/D}$, is a function of the performance gap. It is represented by:

$$f_{R/D} = \frac{1}{1+\exp(-g * G_t)} \qquad \text{(B.22)}$$

At the inflection point, $G_t = 0$ and $f_{R/D}$=0.5. The constant, g, is set at 0.053 in this model. The constant, g, was calculated based on the nonlinear function that was described by the case firms during the interview sessions, see Figure B.1. The starting point for all simulations is set at $TP(t) = AP(t)$, or $G_0 = 0$ so that equal number of research and development projects are approved for the initial quarters.

Figure B.1 $f_{R/D}$ as a Function of Performance Gap



B.1.7.2 Adaptive Capacity

Levinthal and March (1981) proposed that firms will adapt their behavior based on past performance, thus, *Adaptive Capacity* is modeled as a linear function of the performance gap. As the gap increases, adaptive capacity also increases (the worse the firm is performing, the more the openness to new ideas) .

$$AC_{in}(t) = G_t * c_{AC} \tag{B.23}$$

This linear relationship is based on the theoretical model and empirically supported by Lant (1992). It was found that firms base their aspiration levels on the deviation between the targeted goal and the actual performance achieved in the last period. The constant in the Lant study ranged between 0 and 1. In this study c_{AC} was set at 0.10.

The linear relationship described here for *Adaptive Capacity* is then used as a moderator for *Marketing* and *R&D Proficiencies* as described in section B.1.4.

B.2 Vensim Code

Legend:

Stocks noted in *Italics*
Flows noted in Underlined
Auxiliary variable in **Bold**
Constants listed in Table B.1

B.2.1 RESOURCES MODULE (see Figure B.2)

(01) allocation of exploit resources = funded exploitation projects * exploit resources/projects
Units: resources/Quarter
- Resources allocated to exploitation projects

(02) allocation of explore resources = funded exploration projects *explore resources/projects
Units: resources/Quarter
- Resources allocated to exploration projects

(03) **delay for distribution explore** = WITH LOOKUP (Slack Resources)
Units: Quarter
- Delay for distributing available slack resources 2Q

(04) **frac slack resources to exploration** = 1-"frac resources w/equil"
Units: Dmnl
- Slack resources allocated to exploration projects

(05) **frac resource allocation to exploration** = WITH LOOKUP ("GAP: (TARGET-ACTUAL")
Units: Dmnl
- Fraction of resources allocated to exploration activities. 1-frac goes to exploitation activities\

(06) **quarterly slack** = WITH LOOKUP (-"GAP: (TARGET-ACTUAL)" * "perform~ - Slack conversion")
Units: resources/Quarter
- Quarterly slack resources only if the performance gap is negative or actual performance exceed target performance\

(07) resources exploitation = (1-"frac resources w/equil")*resources/quarter
Units: resources/Quarter
- Standard resources to development projects

(08) resources exploration = resources*("frac resources w/equil")/quarter

Units: resources/Quarter
- Standard resources to research projects

(09) *Resources for Exploitation* = INTEG (+slack to exploit+resources exploitation-allocation of exploit resources- "don't use-lose", 0)
Units: resources
- Total resources available for exploitation (development projects),INITIAL = 0

(10) *Resources for Exploration* = INTEG (slack to explore+resources exploration-allocation of explore resources-"don't use-lose explor", 0)
Units: resources
- Resources allocated to new research (exploration) projects, INITIAL = 0

(11) *Slack Resources* = INTEG (slack resources in-slack to exploit-slack to explore, 0)
Units: resources
- Resources not already allocated to other projects

(12) slack resources in = quarterly slack
Units: resources/Quarter
- Resources not previously allocated to other projects

(13) **slack to exploit** = Slack Resources*(1-frac slack resources to exploration)/delay exploit distribution
Units: resources/Quarter
- Slack resources committed to exploitation

(14) slack to explore = Slack Resources*(frac slack resources to exploration)/delay for distribution explore
Units: resources/Quarter
- Slack resources committed to exploration projects

B.2.2 EXPLORATION & EXPLOITATION MODULES (See Figure B.3)

B.2.2.1 Exploration

(15) **catalytic innovations** = funded exploration projects * 0.1 *"mktg-r&d constraint"
Units: projects/Quarter
- Number of catalytic innovations per quarter that result from research projects

(16) **exploration project constraint** = min(Resources for Exploration/"explore resources/ projects", Exploration Projects Requiring Funding)
Units: projects
- Can only undertake projects if (1) resources are available and(2) projects have been approved

(17) *Exploration Projects Requiring Funding* = INTEG (new exploration projects-outdated exploration projects-funded exploration projects, 0)
Units: projects
- Exploration projects that have received approval but have not yet received funding. this is based on the total number of approved projects / quarter INITIAL = 0

(18) failed projects = frac failed exploration*Technology Exploration
Units: projects/Quarter
-Failed research projects

(19) funded exploration projects = exploration project constraint/quarter
Units: projects/Quarter
- Can only undertake projects if (1) resources are available and(2) projects have been approved

(20) inflow integration = successful exploitation projects*0.1*"converter integration/ projects"
Units: integration/Quarter
- Increase in marketing R&D integration as a result of success in exploitation projects

(21) "*Marketing-RD Integration*"= INTEG (inflow integration-outflow integration, 0)
Units: integration
- Marketing & R&D integration stock INITIAL = 10

(22) **"mktg-r&d constraint"** = WITH LOOKUP ("Marketing-RD Integration"*mktgrd switch)
Units: Dmnl
- If integration <0 increase delay time by factor of 2\

(23) new exploration projects = catalytic innovations+("frac resources w/equil")*total approved projects/quarter
Units: projects/Quarter
- Research projects approved per quarter

(24) outflow integration = "Marketing-RD Integration"*"frac. decrease integration"
Units: integration/Quarter
- 1% Outflow of integration per quarter

(25) outdated exploration projects = Exploration Projects Requiring Funding*frac outdated exploration
Units: projects/Quarter

- DELAY FIXED projects that have not received funding in 4 quarters are expired
DELAY FIXED(Exploration Projects Requiring Funding,frac outdated exploration , 0)

(26) successful explore projects = Technology Exploration/delay time
Units: projects/Quarter
- % of research projects that are successful

(27) *Technology Exploration* = INTEG (funded exploration projects-failed projects-successful explore projects, 0)
Units: projects
- Number of projects being undertaken that focus on research efforts, INITIAL=0

(28) **total approved projects** = 6 + ((Slack Resources)/"explore resources/ projects")*STEP(1,8)
Units: projects
- 6 total projects (exploration & exploitation) projects approved quarterly + slack resources available

B.2.2.2 Exploitation

(29) **exploitation projects constraint** = min(Resources for Exploitation/"exploit resources/ projects", Exploitation Projects Requiring Funding)
Units: projects
Exploitation projects can only be undertaken if they have enough resources. this acts as a limiter.

(30) *Exploitation Projects Requiring Funding* = INTEG (new exploitation projects-outdated exploitation projects-funded exploitation projects, 0)
Units: projects
- Exploitation projects that have received approval but have not yet received funding. this is based on the total number of approved projects / quarter INITIAL = 0

(31) <u>failed exploitation projects</u> = (Technology Exploitation*"frac. fail")
Units: projects/Quarter
- Development projects that fail

(32) <u>funded exploitation projects</u> = min(knowledge limitation/quarter, exploitation projects constraint/quarter)
Units: projects/Quarter
- # of development (exploitation) projects that have received resource allocations

(33) new exploitation projects = (1-"frac resources w/equil")*total approved projects/quarter
Units: projects/Quarter
- Exploitation projects approved for the quarter

(34) outdated exploitation projects = Exploitation Projects Requiring Funding*frac outdated exploitation/quarter
Units: projects/Quarter
- DELAY FIXED Projects that do not receive funding within 4Q are expired

(35) successful exploitation projects = Technology Exploitation/delay on exploit
Units: projects/Quarter
- Successful development projects

(36) *Technology Exploitation* = INTEG (funded exploitation projects-failed exploitation projects-successful exploitation projects, 0)
Units: projects
- Number of project underway concerned with exploiting existing technology
INITIAL = 0

B.2.3 KNOWLEDGE MODULE (see Figure B.4)

(37) AC moderating effects = WITH LOOKUP (Adaptive Capacity)
Units: adaptcap
- AC acts as a moderator for R&D & Mktg Proficiencies\

(38) aging innov know = max(0,ZIDZ(Innov Knowledge, aging new to mid))
Units: knowledge/Quarter
- Outdating of knowledge

(39) aging mid knowledge = (Mid Knowledge)/aging mid to old
Units: knowledge/Quarter
- Mid-knowledge aging to old knowledge

(40) **"discount factor AC Mid-Know"** = WITH LOOKUP (Adaptive Capacity)
Units: Dmnl
- When AC = 0 then both new and old knowledge are discounted but not mid knowledge. New knowledge is too risky - not yet proven & old knowledge is outdated – uncompetitive.

(29) **"discount factor AC Old-Know"** = WITH LOOKUP (Adaptive Capacity)
Units: Dmnl
- When AC = 0 then no discount, when AC>0 then discount mid and old knowledge. When AC<0 then do not discount old and mid, d-mid & d-old

(30) **"discount factor AC on I-Know"** = WITH LOOKUP (Adaptive Capacity)
Units: Dmnl
- When AC is >0 then no discount factor d-new =1, if AC<0 then discount new knowledge

(31) forgetting innov knowledge = max(0,forgetting factor new knowledge*Innov Knowledge)
Units: knowledge/Quarter
- Forgetting factor for innovative knowledge

(41) forgetting mid knowledge = Mid Knowledge*"forgetting factor - mid"
Units: knowledge/Quarter
- Knowledge lost

(42) *Innov Knowledge* = INTEG ("knowledge acquired: failed proj"+new knowledge-aging innov know-forgetting innov knowledge,5)
Units: knowledge
- A firm's knowledge base will determine if it can build new products. Assumes no loss of knowledge only outdating. INITIAL = 5

(43) "knowledge acquired: failed proj" = failed exploitation projects*"knowledge~ failed projects"
Units: knowledge/Quarter
- Amount of knowledge gained from failed exploitation projects

(44) **knowledge limitation** = ((Innov Knowledge*"discount factor AC on I-Know") + (Mid Knowledge*"discount factor AC Mid-Know")+(Old Knowledge * "discount factor AC Old-Know"))/"knowledge/ project constant"
Units: projects
- Total stock available. Can't undertake projects unless knowledge is available

(45) *Mid Knowledge* = INTEG (aging innov know-aging mid knowledge-forgetting mid knowledge, 0)
Units: knowledge
- Knowledge of mid-age, INITIAL = 0

(46) new knowledge =(catalytic innovations*"knowledge ~catalytic projects") + ("know explore projects"* (successful explore projects-catalytic innovations)) + ("knowledge~ exploit projects"*successful exploitation projects)
Units: knowledge/Quarter
- Knowledge gained from projects

(47) *Old Knowledge* = INTEG (aging mid knowledge-outdated knowledge, 0)
Units: knowledge
- Knowledge greater than 20Q,INITIAL = 0

(48) <u>outdated knowledge</u> = ZIDZ(Old Knowledge,aging old)+Old Knowledge/aging old/5
Units: knowledge/Quarter
- Knowledge that is outdated and no longer of use to the NPD process

B.2.4 PROFICIENCIES MODULES (see Figure B.5)

(49) <u>"in R&D prof"</u> = new knowledge*"proficiencies~ knowledge converter"*AC moderating effects
Units: proficiencies/Quarter
- Proficiencies increased by new knowledge

(50) *Marketing Proficiencies* = INTEG (mktg proficiency gain-outflow mktg, 0)
Units: proficiencies
- Mktg Proficiencies necessary to launch products

(51) **mktg constraint** = WITH LOOKUP (Marketing Proficiencies)
Units: 1/Quarter
- If Mktg Proficiencies <0, decrease success of launch by a factor of 2\

(52) <u>mktg proficiency gain</u> = new knowledge*"proficiencies~ knowledge converter" * AC moderating effects
Units: proficiencies/Quarter marketing proficiencies gained from new knowledge
- Gain in marketing proficiencies based on moderating factor of adaptive capacity

(53) <u>outflow mktg</u> = loss factor mktg*Marketing Proficiencies
Units: proficiencies/Quarter
- Loss of Mktg Proficiencies over time

(54) <u>"out R&D"</u> = "R&D Proficiencies"*"loss factor R&D"
Units: proficiencies/Quarter
- Loss of R&D proficiencies /quarter

(55) **"R&D constraint"** = WITH LOOKUP ("R&D Proficiencies")
Units: products/project
-If R&D proficiencies<0, projects to products conversion is decreased by a factor of 2\

(56) "*R&D Proficiencies*" = INTEG ("in R&D prof"-"out R&D",10)
Units: proficiencies
- R&D Proficiencies necessary in order to conduct successful projects

B.2.5 RODUCT/PROFITS MODULE (see Figure B.6)

(57) **expenses** ="quarterly cost /explore project"*Technology Exploration
Units: profits
- Expenses incurred by overhead

(58) "*New Products <1*" = INTEG (+product to market-inflow2-obsolete1,7)
Units: products
- Products less than 1 year old, INITIAL = 0

(59) obsolete = Products Launched*(1-frac success launch rate1)
Units: products/Quarter
- Products that do not make it to launch

(60) obsolete1 = "New Products <1"*fracdeath1
Units: products/Quarter
- Aging of new products

(61) obsolete2 = "Products 1-5yr"*fracdeath2
Units: products/Quarter
- Products obsolescing after 5 years

(62) obsolete3 = "Product 6-10 yr"*fracdeath3
Units: products/Quarter
- Obsoleted projects in 3rd period of time

(63) "outflow Prod10+" = "Product 10+"/"aging prod10+"
Units: products/Quarter
aging of products to obsolescence

(64) "*Product 10+*"= INTEG (+ inflow4-"outflow Prod10+", 5)
Units: products
- Products older than 10years, INITIAL = 5

(65) "*Product 6-10 yr*"= INTEG (+inflow3-inflow4-obsolete3, 10)
Units: products
- Products 6-10 years old, NITIAL = 10

(66) product to market = Products Launched*frac success launch rate1
Units: products/Quarter
- Projects converted to products and launched into marketplace

(67) "*Products 1-5yr*"= INTEG (+inflow2-inflow3-obsolete2, 10)
Units: products
- Products 1-5 years old, INITIAL = 10

(68) products from projects = (successful exploitation projects*"conver products/ projects")

Units: products/Quarter
- Projects are converted into products that are launched into the marketplace

(69) *Products Launched* = INTEG (products from projects-product to market-obsolete, 0)
Units: products
- Total number of products in the marketplace, INITIAL = 0

(70) profit outflow = Quarter Profits/quarter
Units: profits/Quarter
drain for profits so that profit does not accumulate on a quarterly basis. Assume -
- Allow profits are used in some fashion

(71) **"profit1-5"** = "Products 1-5yr"*"profit1-5 /product"*"disc pulse 1-5"
Units: profits
- Profits from products 1-5yr old

(72) **"profit10+"** = "Product 10+"*"profit10+ /product"*"discount pulse 10+"
Units: profits
- Profit from products 10+ yrs old

(73) **"profit6-10"** = "Product 6-10 yr"*"profit6-10 /product"*"disc pulse 6-10"
Units: profits
- Profits from products 6-10yr old

(74) **profitnew** = "New Products <1"*"profitnew /product"*disc pulse new
Units: profits
- Profits from new products < 1yr old

(75) profits increase = (("profit1-5"+"profit10+"+"profit6-10"+profitnew)*0.67-expenses)/quarter
Units: profit/Quarter
- Total profits per quarter after expenses of 33% and discounting because of bad products

(76) *Quarter Profits* = INTEG (profits increase-profit outflow, 14)
Units: profits
profits from products, INITIAL = 14

B.2.6 PERFORMANCE GAP & ADAPTIVE CAPACITY MODULE (See Figure B.7)

(77) *Adaptive Capacity* = INTEG ((change in adaptive capacity-drain adaptive)*AC switch, 0.001)

Units: adaptcap
- NPD programs willingness & ability (flexibility & agility) to change strategic direction - 'not broken, don't fix it mentality' INITIAL = 1

(78) change in adaptive capacity = GAP: (TARGET-ACTUAL) * unit conversion
Units: adaptcap/Quarter
- Change in AC based on gap: target-actual. The higher the gap, the greater the increase. Can be negative if gap is less than 0.

(79) drain adaptive =Adaptive Capacity*frac decrease in AC
Units: adaptcap/Quarter
- AC that drains over time through forgetting

(80) change in perf goal = (Perceived Performance: actual - Performance Goal: target)/delay for target adjust
Units: performance/Quarter
- Change in performance goal based on the size of the gap 1:1 change

(81) **"GAP: (TARGET-ACTUAL)"** = ("Performance Goal: target"-"Perceived Performance: actual")*STEP(1,8)
Units: performance
- "target goal - actual goal/ target goal" - the target goal is the performance goal + the aspiration level being driven internally based on stock of old and new knowledge

(82) perceived performance change = perception gap/perception time
Units: performance/Quarter
- Change in perceived performance based on size of gap

(83) *"Perceived Performance: actual"*= INTEG (+ perceived performance change,14)
Units: performance
- Perceived performance is perception time delay of actual performance, INITIAL = 14

(84) perception gap = Quarter Profits*"converter performance /profit"-"Perceived Performance: actual"
Units: performance
- Gap between actual performance & perceived performance

(85) *"Performance Goal: target"*= INTEG (change in perf goal,14)
Units: performance
- Floating goal, initial value INITIAL = 14

Figure B.2 Resources Module

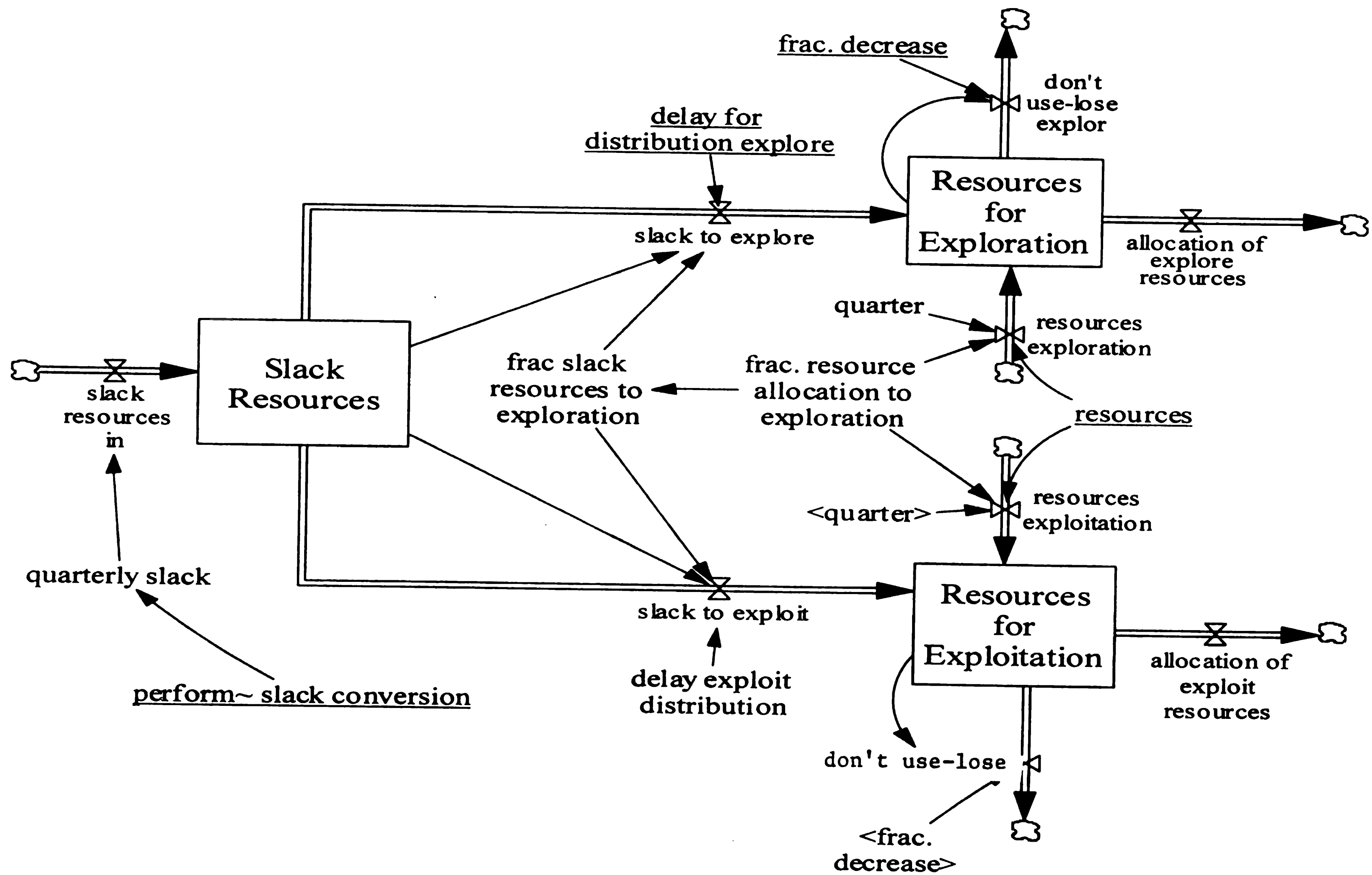


Figure B.3 Exploration Module

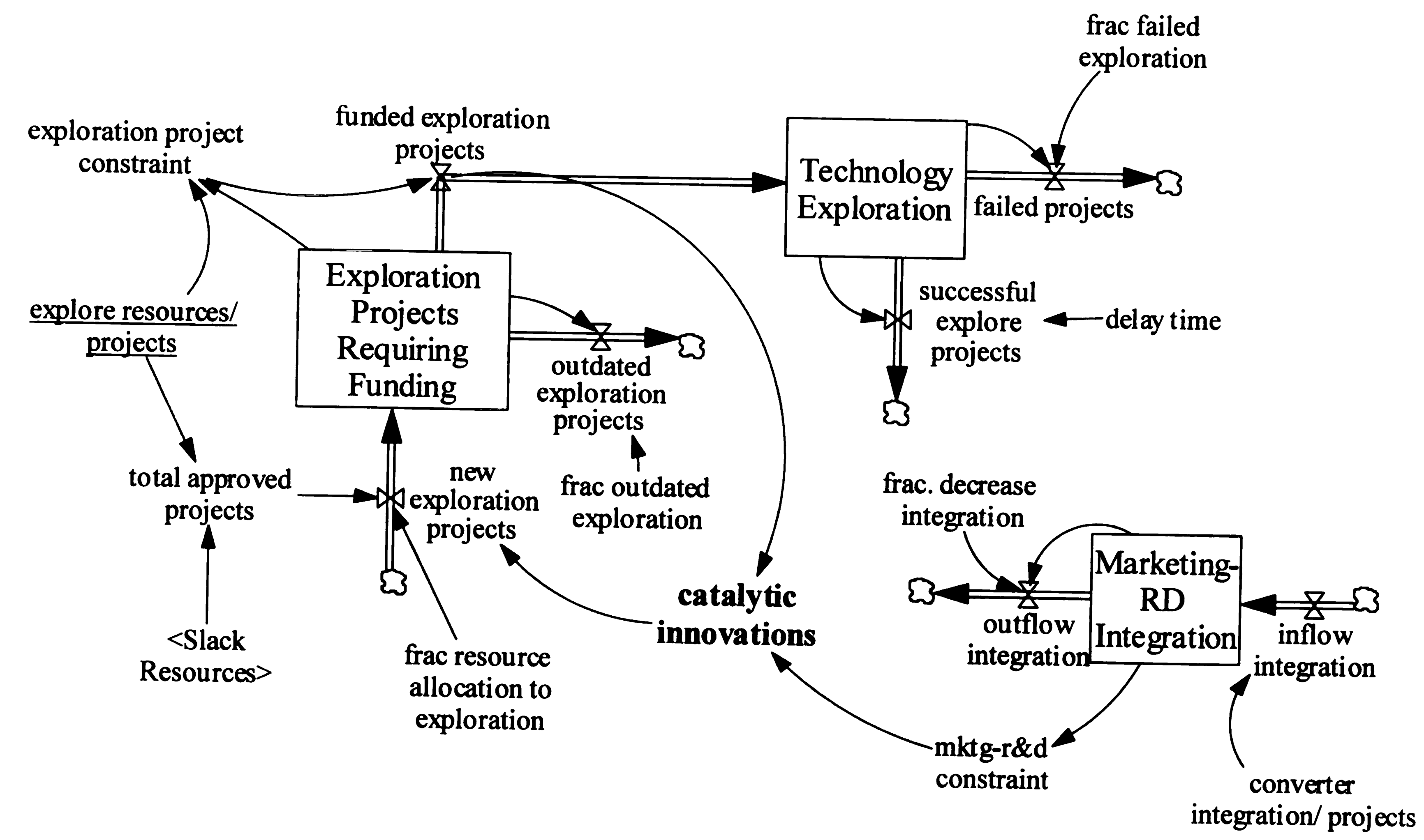


Figure B.4 Exploitation Module

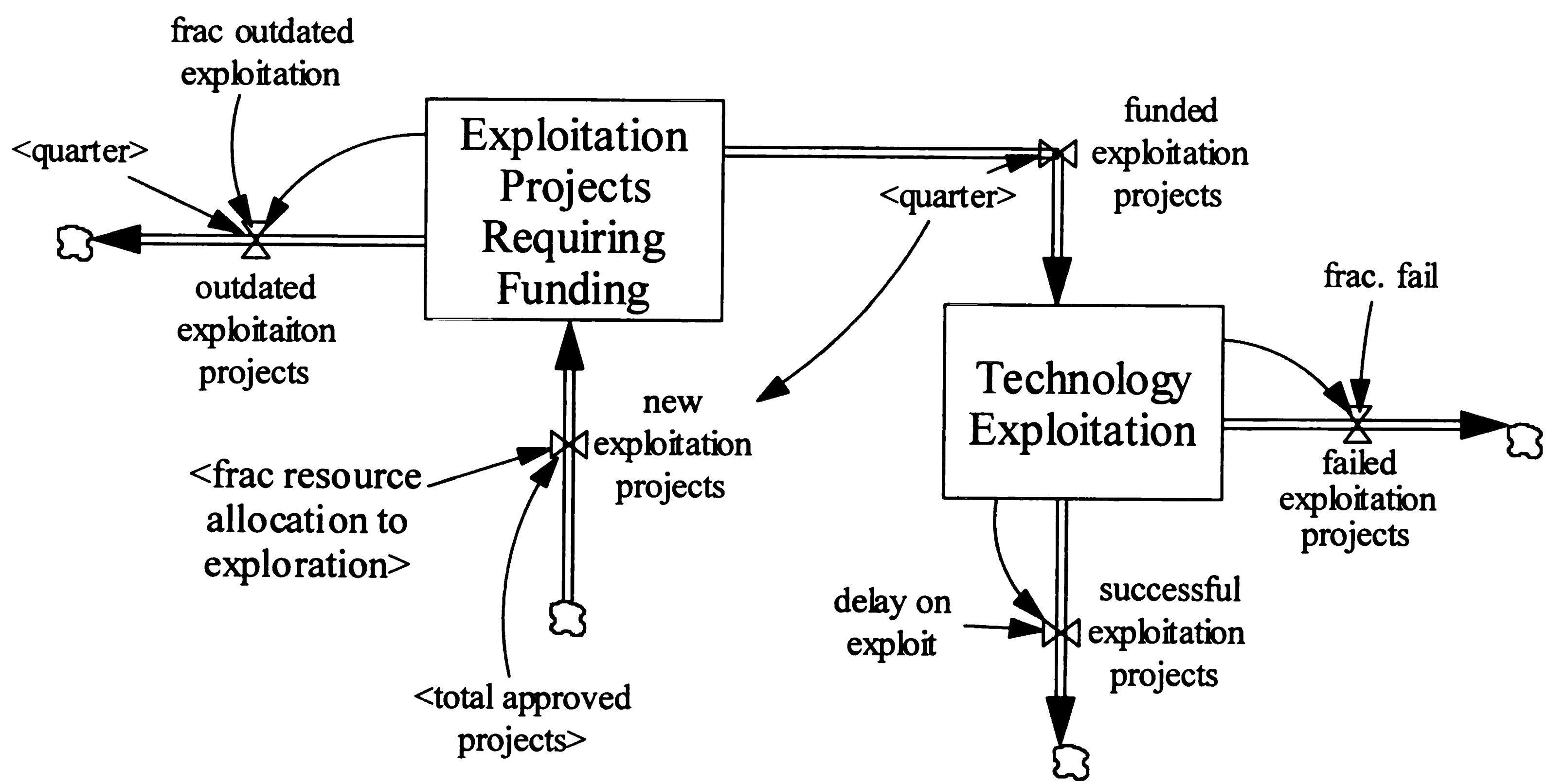


Figure B.5 Knowledge Module

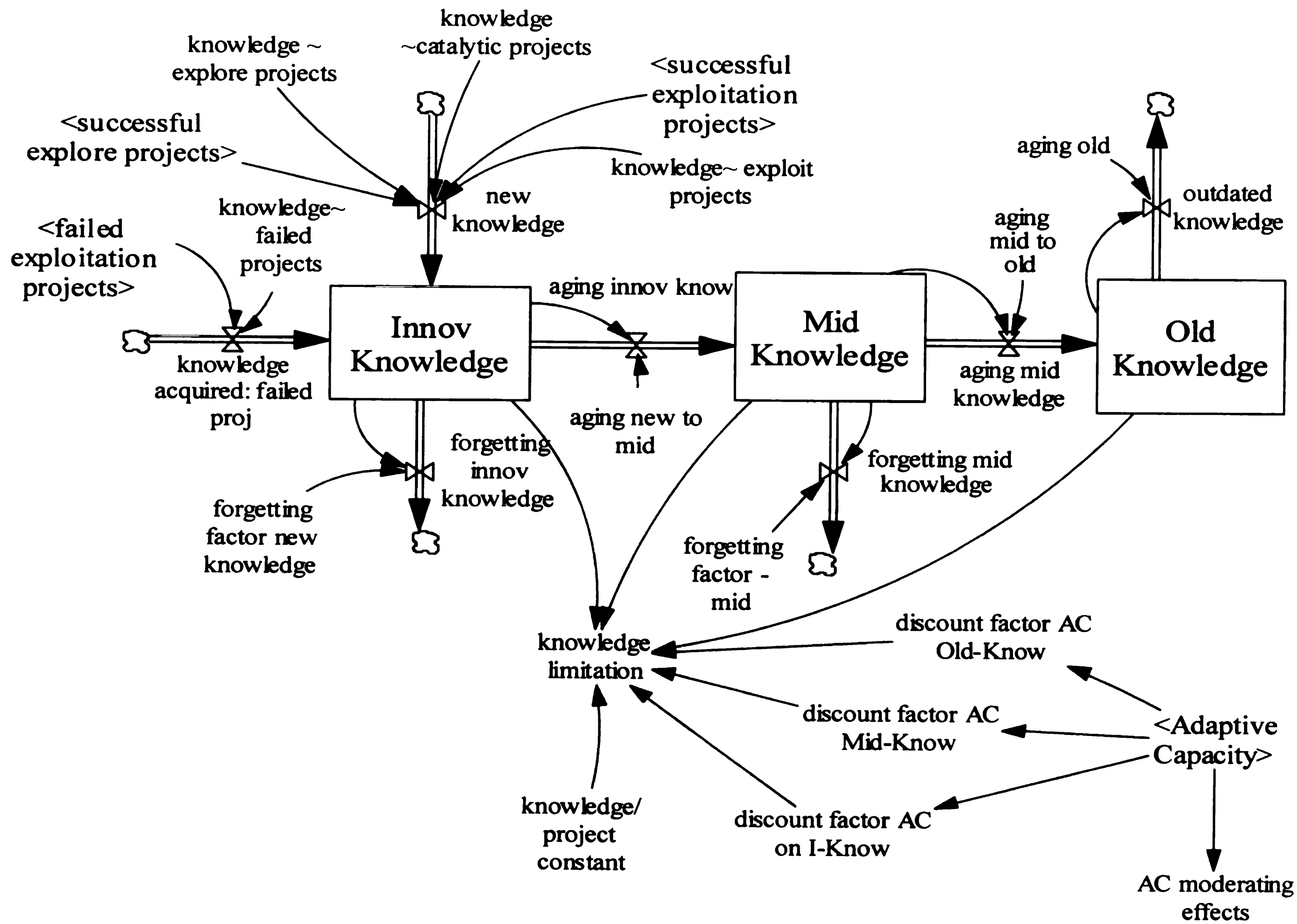


Figure B.6 Proficiencies Module

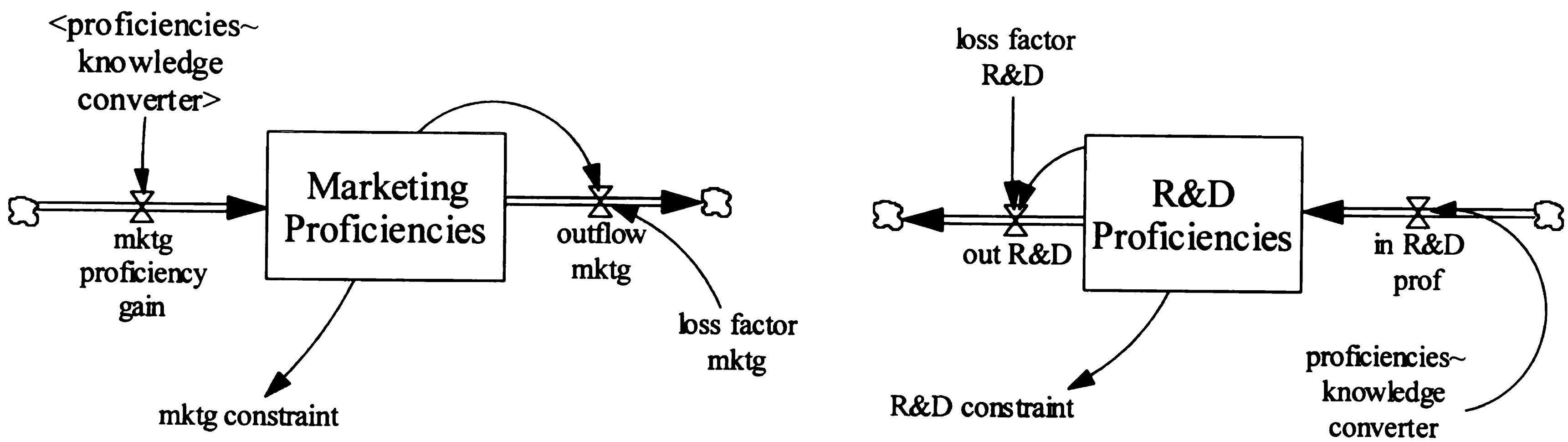


Figure B.7 Profits Module

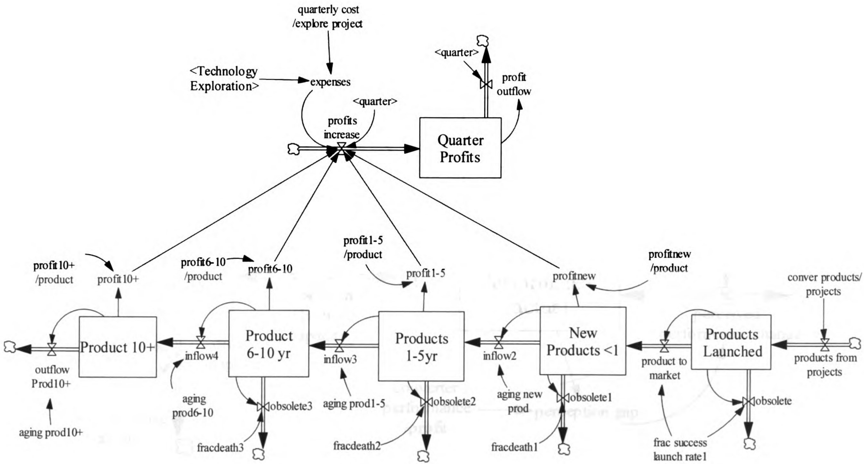
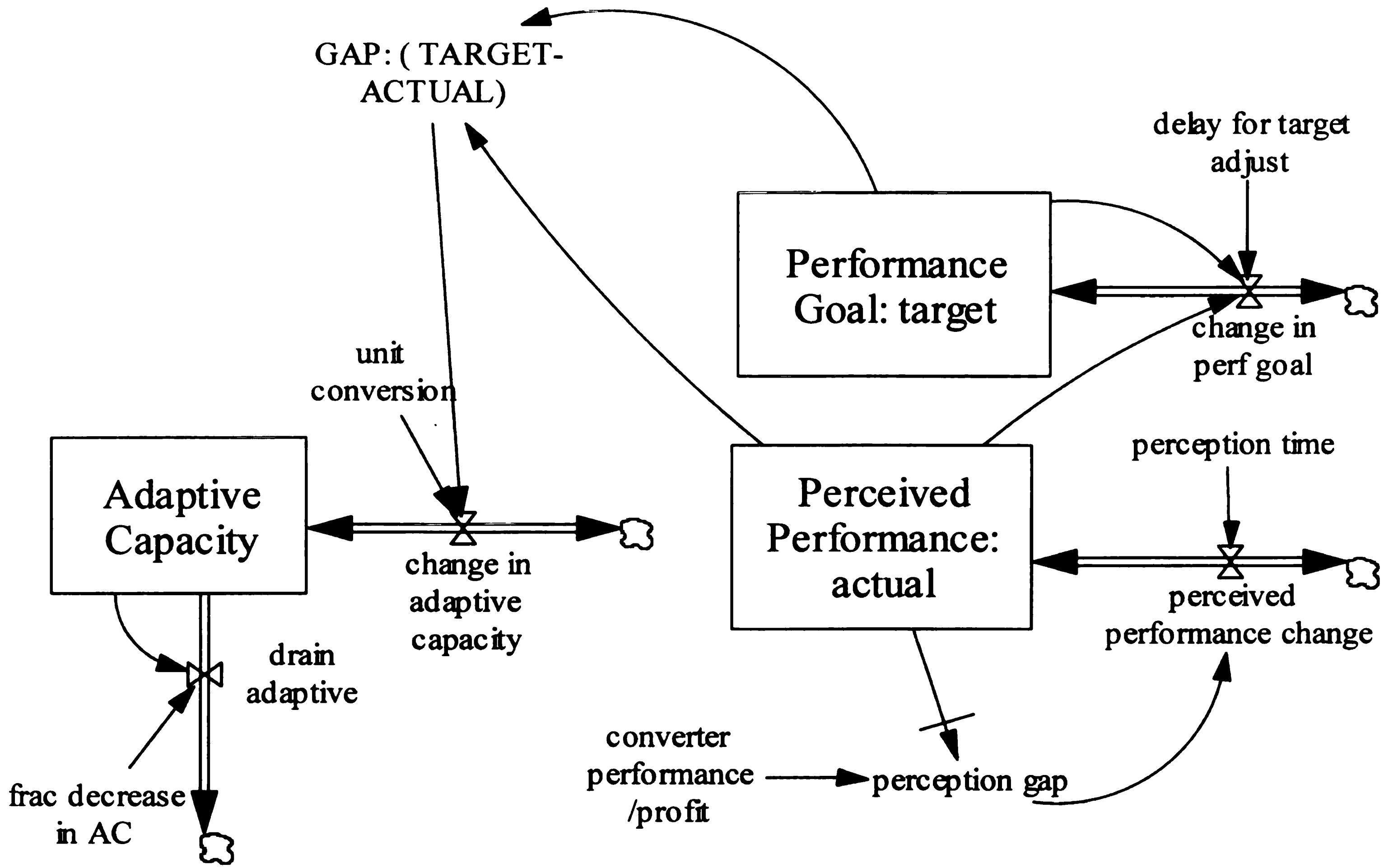


Figure B.8 Performance Gap & Adaptive Capacity Module



APPENDIX C

Longitudinal Study Supporting Documents

C.1 Measures used in the Longitudinal Study (and sources)

Adaptive Capacity	$\overline{x}_{t=1}$	$\overline{x}_{=2}{}^{*}$	$\overline{x}_{=3}{}^{**}$
1. Our firm can quickly change strategic direction based on new technological advances made in our industry. (new) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	5.04 (1.74)	5.47 (1.96)	5.84 (2.29)
2. Our firm can quickly change strategic direction based on new marketing information (i.e., information regarding customers, competitors, or other market changes). (new) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	5.43 (1.32)	6.31 (1.23)	6.96 (2.01)
3. If a major competitor were to launch an intensive campaign targeted at our customers, we would be able to implement a responsive campaign immediately. (Jaworski and Kohli, 1993) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	5.37 (1.36)	5.98 (1.52)	6.35 (2.19)
4. Our firm can quickly change strategic direction based on significant changes in our competitor's pricing structure. (Jaworski and Kohli, 1993) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	4.96 (1.54)	5.71 (1.89)	6.35 (2.14)

*calculated by adding time1 score to time2 change score;
** calculated by adding time2 score to time3 change score

Slack Resources

	$\bar{x}_{t=1}$	$\bar{x}_{=2}^{*}$	$\bar{x}_{=3}^{**}$
1. Capital is a scarce resource for new product development activities in my firm. (Calantone, Garcia, and Droge, forthcoming) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	3.59 (2.04)	3.20 (2.02)	2.63 (2.72)
2. Material supplies are a scarce resource for new product development activities in my firm. (Calantone, Garcia, and Droge, forthcoming) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	3.14 (1.85)	3.10 (2.03)	2.96 (2.41)
3. R&D resources are a scarce in my firm. (Calantone, Garcia, and Droge, forthcoming) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	3.92 (2.02)	3.65 (2.0)	3.29 (2.24)
4. Advertising and promotion resources for new product launches are scarce in my firm. (Calantone, Garcia, and Droge, forthcoming) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	3.55 (1.70)	3.33 (1.77)	2.90 (2.10)

*calculated by adding time1 score to time2 change score;
** calculated by adding time2 score to time3 change score

Marketing-R&D Integration

	$\bar{x}_{t=1}$	$\bar{x}_{=2}^{*}$	$\bar{x}_{=3}^{**}$
1. When developing new or next generation products, information about <u>customers'</u> needs is fully considered. (Li and Calantone, 1998) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	5.73 (1.19)	6.29 (1.50)	6.90 (1.92)

2. When developing new or next generation products, information about <u>competitors'</u> products and strategies are fully considered. (Li and Calantone, 1998) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	5.39 (1.40)	5.80 (1.45)	6.35 (1.75)
3. When developing new or next generation products, market conditions are fully considered in establishing new product development goals and properties. (Li and Calantone, 1998) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	5.06 (1.27)	5.51 (1.73)	6.27 (2.04)
4. Market conditions are fully considered starting from the very early phases in new or next generation product development. (Li and Calantone, 1998) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	4.82 (1.42)	5.33 (1.80)	5.80 (2.04)

*calculated by adding time1 score to time2 change score;
** calculated by adding time2 score to time3 change score

Adoption of Innovations	$\overline{x}_{t=1}$	$\overline{x}_{=2}^{*}$	$\overline{x}_{=3}^{**}$
1. This innovation is currently being used in new product designs. (new based on Tornatzky and Klein, 1982) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	6.37 (0.91)	7.63 (2.0)	8.61 (2.18)
2. Implementing this innovation in our firm has increased efficiency in designing new products. (new based on Tornatzky and Klein, 1982) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	5.49 (1.29)	6.24 (2.0)	6.80 (2.37)

3. Implementing this innovation in our firm has increased technical performance of new products. (new based on Tornatzky and Klein, 1982) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	5.99 (0.87)	7.31 (1.64)	8.27 (2.18)
4. Implementing this innovation in our firm has increased the cost effectiveness of new products. (new based on Tornatzky and Klein, 1982) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	5.49 (1.14)	6.49 (1.96)	7.35 (2.67)

*calculated by adding time1 score to time2 change score;
** calculated by adding time2 score to time3 change score

Knowledge Exploitation	$\bar{x}_{t=1}$	$\bar{x}_{=2}^{*}$	$\bar{x}_{=3}^{**}$
1. Improving our existing manufacturing skills is more important than searching out state-of-the-art manufacturing capabilities. (new, based on March, 1991) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	4.29 (1.44)	5.12 (1.68)	5.76 (2.05)
2. Building competences in our product design process is more important than testing out new methods of developing products. (new, based on March, 1991) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	4.82 (1.24)	5.78 (1.43)	6.53 (1.82)
3. Exploiting our existing in-house technology base is more important than acquiring new, yet unproven technology. (new, based on March, 1991) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	4.76 (1.45)	5.71 (1.62)	6.53 (2.19)

*calculated by adding time1 score to time2 change score;
** calculated by adding time2 score to time3 change score

Marketing Proficiencies

How well does your firm perform the following marketing activities?

	$\overline{x}_{t=1}$	$\overline{x}_{=2}$*	$\overline{x}_{=3}$**
1. Conducting market studies or market research – (i.e., detailed studies of market potential, customer preferences, purchase process, etc.) (Song & Parry, 1997) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	3.24 (1.28)	3.69 (1.75)	4.33 (2.03)
2. Designing and implementing effective advertising campaigns. (new) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	4.35 (1.51)	4.76 (1.88)	5.22 (2.15)
3. Distributing new product announcements. (new) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	4.76 (1.49)	5.27 (1.73)	5.65 (1.98)

*calculated by adding time1 score to time2 change score;
** calculated by adding time2 score to time3 change score

R&D Proficiencies

How well does your firm perform the following engineering/ R&D activities?

	$\overline{x}_{t=1}$	$\overline{x}_{=2}$*	$\overline{x}_{=3}$**
1. Conducting preliminary engineering and technical assessments. (Song & Parry, 1997) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	4.61 (1.38)	5.47 (1.57)	6.24 (1.85)
2. Designing of products to meet designated or revised specifications. (Song & Parry, 1997) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	5.16 (1.26)	6.02 (1.52)	6.78 (1.69)

3. Conducting tests to determine basic performance against specifications. (Song & Parry, 1997) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	5.02 (1.53)	5.82 (1.74)	6.41 (2.11)
4. Continuously designing for cost reduction and quality control. (Song & Parry, 1997) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	4.92 (1.66)	5.80 (1.70)	6.59 (1.88)

*calculated by adding time1 score to time2 change score;
** calculated by adding time2 score to time3 change score

New Product Program Success	$\overline{x}_{t=1}$	$\overline{x}_{=2}^{*}$	$\overline{x}_{=3}^{**}$
1. Relative to your firm's <u>major competitors,</u> how successful has your new product development (NPD) programs been in terms of *profits*? (Calantone, Garcia, and Droge, forthcoming) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	1.06 (1.21)	1.92 (1.64)	2.67 (2.29)
2. Relative to your firm's <u>major competitors,</u> how successful has your firm's NPD programs been in terms of *sales*? (Calantone, Garcia, and Droge, forthcoming) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	0.96 (1.22)	1.67 (1.85)	2.22 (2.36)
3. Relative to your firm's <u>major competitors,</u> how successful has your firm's NPD programs been in terms of *market share*? (Calantone, Garcia, and Droge, forthcoming) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	0.94 (1.27)	1.57 (1.86)	2.10 (2.31)

4. Relative to your firm's objectives, how successful has the NPD program been in the last year in terms of *market share*? (Calantone, Garcia, and Droge, forthcoming) Survey 1 scale: Likert 1 – 7. Surveys 2-3 change score: Likert -3 – +3	0.69 (1.40)	1.04 (1.89)	1.41 (2.65)

*calculated by adding time1 score to time2 change score;
** calculated by adding time2 score to time3 change score

Table C.1 Examples of Innovations Cited by Respondents

- self-cleaning wet vacuum filter
- swing type charger valve
- parallel plate technology
- new molding machine design
- machine for manufacturing of cores
- die system for high speed stamping
- comparison software
- leather drum dye
- rifle scope eye piece
- heat tape
- lithography techniques
- computer-aided design
- current sensor assembly
- appliance leakage sensors
- archive applications

Figure C.1 Example of Knowledge Exploitation as Framed by Adopted Innovations being Tracked Across Time

Please circle the best response for each question.

	INNOVATION1							INNOVATION2							INNOVATION3						
Since adopting <u>this</u> innovation, how has your firm's ability to perform the following engineering /R&D activities changed?	**«Innovation_1»**							**«Innovation_2»**							**«Innovation_3»**						
	Significantly Decreased			Same			Significantly Increased	Significantly Decreased			Same			Significantly Increased	Significantly Decreased			Same			Significantly Increased
1. Focus on improving existing manufacturing skills.	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3
2. Focus on improving product design process.	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3
3. Focusing on new uses for existing in-house technology.	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3

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