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The Impact of Knowledge Inflows on the Performance of National Laboratories in Technological Latecomer Countries

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The Impact of Knowledge Inflows on the Performance of
National Laboratories in Technological Latecomer Countries

by

Patravadee Ploykitikoon

A dissertation submitted in partial fulfillment of the
requirements for the degree of

Doctor of Philosophy
in
Technology Management

Dissertation Committee:
Charles M. Weber, Chair
Timothy R. Anderson
Robert L. Fountain
Antonie J. Jetter

Portland State University
2013

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ABSTRACT

The national laboratories (NLs) play a critical role in the economic and social development of technological latecomer countries, yet no academic study has ever quantified how knowledge inflows and internal knowledge impact the performance of the NLs. This dissertation identifies and ranks the importance of factors pertaining to knowledge inflows and project-internal knowledge, which determine the success or failure of research projects in the NLs of Thailand. A survey of 123 project managers in the NLs, which covers 208 R&D projects, has been conducted. It consists of a questionnaire and unstructured interviews in which the project managers discuss their project(s). Data from the questionnaire are analyzed by factor analysis, multiple regression and logistic regression; qualitative data from the interviews are used to interpret the quantitative results from the questionnaire.

The research finds that, regardless of a project's mission, knowledge inflows from outside the project group impact performance more significantly than knowledge from inside the project group does. Second, the capacity of R&D project groups within the NLs to absorb knowledge from external sources is very selective. Absorptive capacity does not just pertain to prior related knowledge; it is also a function of the source of external knowledge, the knowledge pathway into the project group, the source of complementary or substitutive knowledge that resides within the project group, and the mission to which the knowledge contributes. Third, the NLs face an ambidexterity

challenge that is commonly observed in private industry—exploiting current capabilities interferes with the national laboratories’ capability to explore.

The discovery of *selective absorption* of knowledge provides practicing managers with a toolkit of micro-levers with which they can enhance performance as measured by a variety of metrics in highly specific ways. The dissertation also proposes and validates a theoretical framework for knowledge management that decomposes the national laboratory system into nine knowledge subsystems, which can be managed at a relatively low level of the organization. The methods by which this research has been conducted can be used as a tool to benchmark how knowledge management practices in different R&D organizations and environments impact performance. Guidelines for structural adjustments to the national innovation system, which are based on these contributions, should enable policymakers in most countries to implement an Open Innovation program for their national laboratories and enhance the ambidexterity of their organizations.

DEDICATION

*To my advisor, Dr. Charles M. Weber, who
believed there was something to my initial idea,
helped me dig deep to discover the phenomena,
and pointed out the contributions of these discoveries.*

Also,

*to anyone who believes in and supports a new approach,
opens his/her mind to new ideas,
and works hard to make things better.*

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GLOSSARY OR LIST OF ABBREVIATIONS/SYMBOLS

NLs = national laboratories

LTUs = Local Technology Users

TLCs = Technology Latecomer Countries

ORDU = Other Research and Development Units (Groups)

LocUniv = Local Universities (Domestic Engagement)

InatSrc = International Sources

PrExp = Prior Experience

PrKn = Prior Knowledge

PILAs = Project Internal Learning Activities

VLAs = Vicarious Learning Activities

CLAs = Contextual Learning Activities

NIS = National Innovation System

IP = Intellectual Property

NPSD = New Product and Service Development

RG = Research gap

RQ = Research question

HP = Hypothesis

DV = Dependent variable

IV = Independent variable

FIV = Factor of independent variables

MV = Moderating variable

FMV = Factor of moderating variables

NLKMS = National Laboratories Knowledge Management System

NLKMSs = National Laboratories Knowledge Management Subsystems

1. INTRODUCTION

1.1 RESEARCH PROBLEM

The national laboratories (NLs) in countries that are latecomers to advanced technological development are considered a significant source of scientific knowledge and technology for local industries that the national government deems strategic and for public agencies that are engaged in developing the country's infrastructure (*e.g.*, L. Kim, 1997; P. L. Chang & Hsu, 1998; Arnold *et al.*, 1998; Gu, 1999; Intarakumnerd *et al.*, 2002; Mazzoleni & Nelson, 2007). In these countries, most private industrial firms and government agencies lack the financial and human capital to perform applied research and to develop technologies internally (L. Kim, 1993; Hou & Gee, 1993; Intarakumnerd *et al.*, 2002; Hipkin, 2004; Chaminade & Vang, 2008). Therefore, the primary mission of the national laboratories is to adopt foreign (Arnold *et al.*, 1998; King & Nowack, 2003; Fu *et al.*, 2011) and domestic (Nass *et al.*, 2007; Mazzoleni & Nelson, 2007; Fu *et al.*, 2011) technological knowledge and adapt it to the needs of critical local users of technology (Howells, 1990; Lall, 1992; Mazzoleni & Nelson, 2007). Local technology users (LTUs) in private industry rely on the availability of this customized knowledge to provide products and services for domestic consumption and for export (L. Kim, 1993; Hou & Gee, 1993). Their profitability and international competitive position consequently depend upon how well the national laboratories perform their mission of knowledge adoption and adaptation.

The national laboratories (NLs) in technology latecomer countries (TLCs) perform two other critical missions as well. They build capabilities in research and development that exceed the LTU's current needs, in order to generate an experience base for the demands of the future, when the country desires to be at a much more advanced level of economic and technological development (Mazzoleni & Nelson, 2007). They also perform a mission in their own right – they transfer technology that they develop, providing the national laboratories with a source of revenue (Arnold *et al.*, 1998).

To succeed at these three missions, the national laboratories must obtain knowledge from external sources by engaging in learning activities that span organizational boundaries (Ancona & Caldwell, 1992; Freeman, 1995; Lundvall, 1992b; Lundvall, 2010). They must subsequently combine the knowledge gained from these inflows with knowledge that is already present or being created within their organizations and project groups. The resulting knowledge is integrated into the technologies that the national laboratories customize and subsequently transfer to LTUs; the technologies that they develop and commercialize; or the research capabilities that they build up for the future of the nation.

The national laboratories in technology latecomer countries are much more dependent on external sources of knowledge than their counterparts in more advanced countries because they have accumulated insufficient knowledge and experience to develop advanced technologies internally (L. Kim, 1993; Hou & Gee, 1993; Intarakumnerd *et al.*, 2002; Hipkin, 2004; Chaminade & Vang, 2008). This deficit in internal expertise inhibits their ability to absorb knowledge from external sources (W. M. Cohen & Levinthal, 1990; Lane & Lubatkin, 1998; Zahra & George, 2002; Mowery & Oxley, 1995; Keller,

1996; Todorova & Durisin, 2007). As a result, the gap in performance between the national laboratories in technological latecomer countries and their counterparts in the more developed countries may be larger than one would expect.

If the national laboratories do not manage their knowledge inflows successfully, then they cannot succeed at the three previously mentioned critical missions. The knowledge that the NLs accumulate, the technologies that they develop for commercialization and the research capabilities that they build up for the future remain within their institutional boundaries and do not transfer to the organizational entities that put them to use. Or, even worse, the NLs may not even be able to adopt the scientific and technological knowledge that they need to customize for their LTUs. In either case the LTUs, the primary customers of the NLs, would not benefit from the efforts of the NLs. A substantial portion of the budget of the NLs would be regarded as misallocated,¹ and the purpose of NLs in TLCs could be called into question.

Given the important role the national laboratories play in the economy of technology latecomer countries, it can be argued credibly that the performance of national laboratories has a significant impact on the welfare of the population and national economic development (Park, 1998; Mazzoleni & Nelson, 2007; Fu *et al.*, 2011). One would therefore surmise that the impact of knowledge inflow on the performance of national laboratories would be well understood, or at least have been a subject of

¹In TLCs, gross domestic expenditure on research and development (GERD) amounts to about 0.25% of GDP, and the annual budgets for NLs constitute about 40% of GERD (UNCTAD, 2005; UNESCO, 2011). A misallocation of a substantial portion of the budget of the NLs could be on the order of *hundreds* of millions of dollars over a period of a few years.

extensive study. Yet, surprisingly, this is not the case. Instead, most studies related to the roles of national laboratories in latecomer countries have been investigated at the system level of national innovation by analyzing a single case (L. Kim, 1993; Intarakumnerd *et al.*, 2002; P. K. Wong, 2003; Hadjimanolis & Dickson, 2001) or by using multi-case analysis (Nelson, 1993; Dahlman & Nelson, 1995; Arocena & Sutz, 2000; Arocena & Sutz, 2005; Gu, 1999; Lundvall *et al.*, 2002). Some potential success factors have been identified (Arnold *et al.*, 1998; Gu, 1999; Intarakumnerd *et al.*, 2002; Mazzoleni & Nelson, 2007), but not validated. It can thus be argued that the exogenous factors that drive the successes of national laboratories are not really understood to the extent where the NLs can prevent gross misallocation of resources, build up an enhanced national research capability or generate substantial revenue from commercializing technology that they have developed. Opportunities to investigate how external engagement by national laboratories impacts their performance consequently do not just abound – the need to conduct such research is compelling.

1.2 KNOWLEDGE INFLOWS

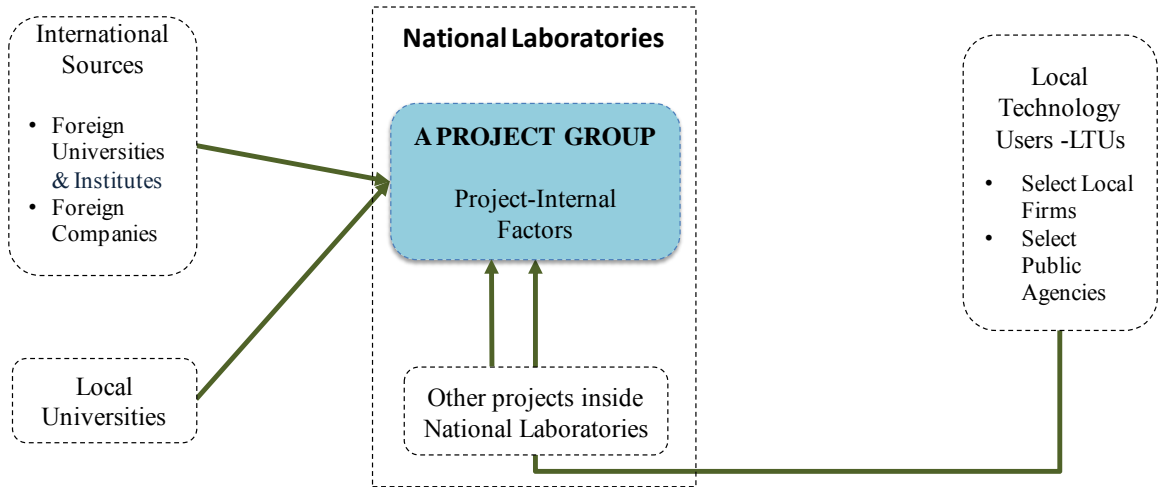


Figure 1.1: Sources of knowledge for a project group within the national laboratories in technology latecomer countries. (integrated from Utterback, 1975; Mazzoleni & Nelson, 2007; Hoekman *et al.*, 2005; Encarnaç o, 2007; Lundvall, 2010; Ancona & Caldwell, 1992).

Figure 1.1 depicts the critical sources of knowledge that are available to a project group within the national laboratories in technology latecomer countries. The arrows indicate knowledge inflows into a particular project group within the national laboratories. Figure 1 shows that knowledge can come from within the project group itself. It could have been available to the group prior to the beginning of the project (Huber, 1991), or it can be created by deliberate learning efforts while the project is ongoing (e.g., Adler & Clark, 1991; Bohn, 1994; Lapr e *et al.*, 2000; Edmondson *et al.*, 2003). Other projects within the national laboratories can serve as sources of knowledge, if project groups within the NLs

engage in learning activities that span organizational boundaries (Ancona & Caldwell, 1992; Freeman, 1995; Lundvall, 1992a; Lundvall, 2010). Knowledge can flow into project groups within the NLs from sources that are outside the NLs but within the country's national innovation system. These sources include local universities that provide local scientific and technological knowledge, as well as the LTUs, which provide feedback on the technologies that the NLs deliver and information about the use environment (von Hippel, 1988) of these technologies.² Sources outside the national innovation system include foreign universities, national laboratories in other countries and multinational corporations (MNCs).

1.3 PURPOSE OF DISSERTATION

The purpose of this dissertation is to investigate how knowledge inflows into the national laboratories of technological latecomer countries affect the performance of national laboratories. In particular, I would like to *identify factors pertaining to knowledge inflows that determine the success or failure of research projects in the national laboratories of latecomer countries*. I am thus effectively addressing the following management question: “How can managing knowledge inflows improve the performance of research projects at the national laboratories in technological latecomer countries?”

² The academic literature does not consider local technology providers from the private sector that are not local technology users as a critical source of knowledge to the national laboratories in technology latecomer countries.

The success of a national laboratory is contingent upon the number of research and development projects that it completes and the perceived impact that these projects have on the bottom-line of LTUs and the wellbeing of the country at large (L. Kim, 1980; L. Kim, 1997; P. L. Chang & Hsu, 1998; K. Lee & Lim, 2001). I consequently make the R&D project my unit of analysis, and I try to identify the factors that make these projects successful. My primary focus is to identify the success factors that involve knowledge inflows. However, I include sources of internal knowledge in my study, because they tend to impact the relationship between knowledge inflow and the performance of the research project. I am primarily interested in ranking the relative impact of success factors that affect the performance of research projects within national laboratories. This ranking will give project managers the ability to develop a strategy for engaging effectively with the various sources of knowledge that affect the project's performance. The managers will be able to prioritize their engagement with the various sources of knowledge that are available to them.

It is well known that an organization's internal knowledge or internal learning activities can enhance the organization's capacity to absorb knowledge from external sources (W. M. Cohen & Levinthal, 1990; Kogut & Zander, 1992; Lane & Lubatkin, 1998; Zahra & George, 2002; Mowery & Oxley, 1995; Keller, 1996; Todorova & Durisin, 2007; Griffith & Sawyer, 2009; Nemanich *et al.*, 2010), and in an organization as complex as the national laboratories the sources of external knowledge and the sources of internal knowledge can be highly diverse. A study of knowledge inflows into the national laboratories must therefore consider the possibility that some forms of internal

knowledge enhance the absorptive capacity for certain types of external knowledge more than others do. Some interactions could even diminish the capacity to absorb external knowledge. The performance of the national laboratories could thus depend upon a plethora of interactions between its various internal and external sources of knowledge. These interactions and their impact on performance have yet to be clearly articulated or subjected to rigorous academic study, even though doing so could make a significant contribution to management practice. An improved understanding of which interactions have the strongest impact on performance would give the managers of the national laboratories a toolkit of micro-levers that they can pull selectively to achieve specific goals. It is also the purpose of this dissertation to identify these micro-levers.

1.4 DISSERTATION OUTLINE

The organization of the dissertation consists of an introduction, a literature review that leads to a conceptual framework, a set of testable hypotheses, a discussion of research methods, a chapter that presents the results of the study and another that presents its conclusions. The final chapter will identify some of the study's limitations. It will also review the study's contributions, discuss theoretical and practical implications of the study and make suggestions for further research.

1.4.1 Chapter 1 – Introduction

Chapter 1 familiarizes the reader to the dissertation topic. The first section describes the research problem, and the second introduces the concept of knowledge flows. Both

sections argue that the study that the dissertation proposes should be performed. The purpose of the dissertation is discussed in the third section. The fourth section presents an outline of the dissertation.

1.4.2 Chapter 2 – Literature Review

Chapter 2 explains the academic background of the study. The literature review in this chapter covers six sections. The first section reviews the three missions of NLs within the National Innovation System (NIS) of technological latecomer countries (TLCs) in order to understand the purposes of NLs and how NLs assess their successes. The second section reviews sources of knowledge and pathways to gain knowledge from both internal and external sources of NLs in TLCs. The purpose of this section is to identify sources and pathways of knowledge inflows into NLs in TLCs. The third section discusses broadly based issues pertaining to how obtaining knowledge from external sources impacts the performance of research and development units at the organization level and at the project level. The purpose of this section is to show how prior studies have measured the impact of external knowledge on organizational performance. This section also identifies the overriding academic research gap for this dissertation. The fourth section of chapter 2 reviews factors that impact knowledge inflows at the project level. The purpose of this section is to refine the focus of this dissertation to the project level and to identify related gaps in the academic literature. The fifth section presents the theoretical framework that has emerged from the literature search. The empirical study that I shall conduct as part of this dissertation tests this theoretical framework. The sixth

section summarizes the research gaps that have been identified in the literature review and states the research questions that pertain to these gaps.

1.4.3 Chapter 3 –Hypotheses

Chapter 3 identifies the research hypotheses that will be tested empirically in this dissertation. These hypotheses focus on how knowledge inflows impact the performance of R&D projects at the NLs in TLCs. In these hypotheses the degree of engagement with the source of external knowledge acts as a proxy measure for the amount of knowledge that flows into a particular project group from a particular source. Four external sources of knowledge will be considered: other R&D project groups within NLs, local universities, local technology users (LTUs) and international sources of knowledge. In addition, this chapter sets up hypotheses pertaining to the degree that internal knowledge (knowledge that resides within or is created within the project group that performs the R&D) influences the impact of external knowledge on the performance of R&D projects.

1.4.4 Chapter 4 – Research Methods

Chapter 4 describes the research methods that I use in my dissertation. This description includes discussions of the unit of analysis (R&D project groups); the setting of the study (the national laboratories of Thailand); variables and measures; data collection (survey plus interviews with project managers and project evaluators); validity and reliability; and the approaches to data analysis that are deployed in the study (factor analysis and a hierarchical approach to multiple regression).

1.4.5 Chapter 5 – Results

Chapter 5 of this dissertation presents the results of the empirical study. The first section displays and describes the descriptive statistics. The second section details the output of a factor analysis that was performed on the predicting variables and a correlation matrix of predictors and output variables that reflect performance. The third section benchmarks the explanatory power of the multiple regressions and the logistic regressions that were conducted for each performance metric. The fourth section discusses the results of the hypothesis tests that characterize how factors that pertain to knowledge inflow and factors that pertain to internal knowledge affect performance. The fifth section discusses the interactions between these factors.

1.4.6 Chapter 6 – Conclusions

Chapter 6 draws conclusions by synthesizing quantitative results from chapter 5 with data that was obtained from interviews with project managers and project evaluators. In the first section, I draw conclusions that are specific to the setting of my study. In the second section, I present the overarching conclusion of this dissertation—a framework for knowledge flows for the part of the national innovation system that pertains to the national laboratories. In the third section, I conclude that absorption of knowledge is selective—it depends on the source of external knowledge, the source of internal knowledge enables the absorption of knowledge, the interaction between those sources, the type of knowledge inflow and the mission to which it is applied. I argue that knowledge flows, as they pertain to the national laboratories, can be organized into

knowledge subsystems of the national innovation systems, which can be managed at a relatively low level within the national laboratories. In the fourth section, I present the knowledge subsystems that are associated with each of the output variables of my research, and I draw conclusions that are specific to each of the three primary missions of the national laboratories. The fifth section discusses the alignment of the mission-specific criteria and their linkage to organizational ambidexterity (*e.g.*, Tushman & O'Reilly, 1996). In the sixth and final section, I present conclusions about the knowledge subsystems of the national laboratories system that pertain to specific sources of knowledge, and I discuss the relative importance of external and internal sources of knowledge.

1.4.7 Chapter 7 – Summary, Contributions and Limitations

I summarize my research in the last chapter of my dissertation. In the first section, I restate the research questions and report on how they have been addressed by the findings of my research. In the second section, I examine the theoretical implications of the findings from my study. I discuss how this dissertation has contributed to academic research in various sub-fields of technology management and in other, related fields of study. In the third section, I show how findings from this dissertation have revealed management practices that are particularly useful for national research laboratories in technological latecomer countries. In the fourth section, I discuss how findings from this dissertation may have implications for national policy in technological latecomer countries, yet I make the argument that the findings of my study can be generalized beyond technological latecomer countries and beyond the national laboratories setting, if

proper follow-on studies are conducted. In the fifth section, I identify some of my study's limitations, and I suggest how they can be overcome through further research using methods that I have in part developed in this dissertation. In the last section, I describe the methods contribution that should enable these follow-on studies.

2. LITERATURE REVIEW

The management question that motivates this dissertation is: “*How can managing knowledge inflows improve the performance of research projects at the national laboratories in technological latecomer countries?*” This question is viewed in the context of the three most important missions of national laboratories (NLs) in technological latecomer countries (TLCs), which have been identified as

- 1) Adopt foreign and domestic technological knowledge and adapt it to *the needs of critical LTUs*;
- 2) Generate revenue *for themselves* by commercializing technology that they have developed; and
- 3) Build R&D capabilities *for the future needs of the country*. This context raises a series of issues, which have been debated in the academic literature.³

³ The following issues, which are addressed in section 2.1, are of particular interest to practicing managers within the NLs in TLCs:

- 1) How do NLs affect new product and service development in TLCs? (Mission 1)
- 2) How do NLs in TLCs generate revenue for themselves from the technology that they develop? (Mission 2)
- 3) How do NLs in TLCs retain and enhance their capabilities for the benefit of national technological and economic development? (Mission 3)

My focus on knowledge inflows raises the following issues, which are addressed in section 2.2:

- 4) What is the nature of the sources of knowledge for project groups within the NLs in TLCs?
- 5) What are the pathways for knowledge inflow into the project groups within the NLs in TLCs?

My research also raises some broadly based issues pertaining to knowledge inflow in research and product development, which are addressed in sections 2.3 and 2.4.

- 6) How does managing knowledge inflow impact the performance of research organizations and development organizations (section 2.3)?
- 7) How does managing knowledge inflow improve the performance of research and development at the project level (section 2.4)?
- 8) What factors are important to managing knowledge flow? For example, what organization-internal factors enable or hinder knowledge inflows, knowledge outflows and technology transfer (section 2.4)?

In the review of the academic literature that follows, I hope to identify gaps in knowledge that warrant further scientific study. From these gaps, I shall generate research questions for my dissertation. The major contributions of this dissertation will be closing the gaps in knowledge that I identify in this chapter, and addressing the research questions that they generate.

In the following sections, I discuss each of the abovementioned issues one by one, and I identify the literature stream in which the issue has been discussed. The discussion of each issue leads to a model of the issue that is grounded in literature. At the end of the literature review, these individual models are assembled into a model of how knowledge flows into and out of the national laboratories of technology latecomer countries. This model will be tested in the empirical study that I propose for my dissertation.

2.1 THE NATIONAL LABORATORIES WITHIN THE NATIONAL INNOVATION SYSTEMS OF TECHNOLOGY LATECOMER COUNTRIES⁴

To succeed at their three critical missions, the national laboratories, in TLCs and elsewhere, must be linked to and interact effectively with their national innovation systems (NIS), “the network of institutions in the public and private sectors whose

⁴ In this section of the literature review, I look at the role that national laboratories play within the national innovation systems of technology latecomer countries. I focus on the three critical missions of the NLS in TLCs. I address issues that are of particular interest to the managers of NLS in TLCs: how do NLS affect new product and service development in TLCs; how do NLS in TLCs retain and enhance their capabilities for the benefit of national technological and economic development; and how do NLS in TLCs generate revenue for themselves from the technology that they develop? Most of the articles that are reviewed in this section come from the literature on national innovation systems. However, I also draw on the literature on technology transfer, absorptive capacity and new product development.

activities and interactions initiate, import, modify and diffuse new technologies” (Freeman, 1987, as cited by OECD, 1997). These linkages and interactions, within and across organizations that are located within or rooted inside the borders of a nation state, are a prerequisite for success in innovation – they produce, diffuse and use new economically useful knowledge (Lundvall, 1992a, p. 325). These linkages may be technological, commercial, legal, social and financial in nature, and they facilitate the “development, protection, financing or regulation of new science and technology” (Niosi *et al.*, 1993 p. 139). As a result, “the interactions of these institutions determine,” to a significant degree, “the innovative performance of national firms” (Nelson, 1993 p. 4). They are also said to enhance the national absorptive capability (Dahlman & Nelson, 1995; Lall & Narula, 2004; Narula, 2004; Roper & Love, 2006), which Dahlman and Nelson (1995, p. 88) define as “the ability to learn and implement the technologies and associated practices of already developed countries.” The linkages and interactions within national innovation systems are critical to national economic development, because they improve learning efficiency, which is the source of innovativeness of a nation (Nelson & Rosenberg, 1993; Lundvall, 1992a). They also allow innovation to occur more rapidly and in a direction that meets the needs of the people of the country (European_Commission, 2009).

The institutions within the national innovation system may vary by economic structure of each country, but normally include private industrial firms, the public sector, the financial sector and public research organizations (Lundvall, 2010, p. 14). Private firms can be local companies or multi-national corporations. They are considered production units

that engage in interactive learning across organizational boundaries (B. H. Johnson, 1992). The public sector helps shape the institutional set-up and the overall structure of production within the NIS, and it will engage in occasional intervention. Its primary role is to promote self-organized learning by the various institutions that comprise the national innovation system; the intent is to make the NIS more open the rest of the world (Dalum, 1992). The public sector may also play the role of a very large user of various products, especially in situations of high technological uncertainty and market risk (Gregersen, 1992 in Lundvall 1992, pp. 133-150). It can also act as a competent lead user (von Hippel, 1986) that is able to communicate use information in a form that helps the providers of technology, the NLs, to adapt technology to the needs of mainstream users (Lundvall, 1985 cited by Gregersen, 1992; 2010, p. 134). Financial institutes are a source of loans for innovation. Government may collaborate with financial institutions to provide special interest rates or credit for investment in innovation (Christensen, 1992, pp. 146-168). Finally, public research organizations including universities and national laboratories act as sources of technology within NIS (Freeman, 1992, pp. 169-186).

Continuous interaction with the various elements of the national innovation system allows industrial firms continuously upgrade their technological competences. Unless they do so, “their profits and growth are likely to decline as markets continue to be captured by innovative firms in competitor nations. The speed and effectiveness of the flows of innovation into firms are critical determinants of the economic success not only of individual firms but also of groups of firms, localities and regions, nations and trading blocs of nations” (Dodgson & Bessant, 1996, p. 11). Dodgson and Bessant (1996) also

argue that effective innovation consists of an exchange of “knowledge of innovation between the ‘science base’ of research and development undertaking bodies -- higher education institutes, private and public sector research and technology organizations -- and industrial firms,” as well as “between firms of different sizes and character.” Such exchanges are “essential for all these different economic agents to build up the competences they need to differentiate themselves in markets, and thereby to be competitive.” (ibid, 1996, p. 11)

National governments in technology latecomer countries have been trying to advance national innovation systems as a framework for economic and social development (Nelson, 1993; Gu, 1999; Arocena & Sutz, 2000; Lundvall *et al.*, 2002; Intarakumnerd *et al.*, 2002; Mazzoleni & Nelson, 2007), as they believe that the potential of science and technology will lead to economic and social development in their countries (Gu, 1999). Government policies in TLCs are also designed to enhance the national absorptive capability (Dahlman & Nelson, 1995; Lall & Narula, 2004; Narula, 2004; Roper & Love, 2006), allowing innovation to occur more rapidly and in a direction that meets the needs of the people of the country (European Commission, 2009). The national laboratories in TLCs act as an enabler of technology within the TLC’s national innovation system, like they do in many more advanced countries (Freeman, 1992, 2010, p. 173). In the process, they tend to play a lead role in the implementation of science and technology policies that the government considers beneficial to both the public sector and private industry (Nelson & Rosenberg, 1993).

The national laboratories in technology latecomer countries are much more dependent on external sources of knowledge than their counterparts in more advanced countries because they have accumulated insufficient knowledge and experience to develop advanced technologies internally (L. Kim, 1993; Hou & Gee, 1993; Intarakumnerd *et al.*, 2002; Hipkin, 2004; Chaminade & Vang, 2008). This deficit in internal expertise inhibits their ability to absorb knowledge from external sources (W. M. Cohen & Levinthal, 1990; Lane & Lubatkin, 1998; Zahra & George, 2002; Mowery & Oxley, 1995; Keller, 1996; Todorova & Durisin, 2007). As a result, the gap in performance between the national laboratories in technological latecomer countries and their counterparts in the more developed countries may be larger than one would expect.

The overall performance of national laboratories in technology latecomer countries depends upon how well they succeed at their three most important missions. If the NLs perform their first mission well, then they enhance LTUs ability to develop new products and new services both rapidly and effectively (Dodgson & Bessant, 1996). If the NLs do well at the second mission, they are able to supplement their budget for discretionary activities.⁵ If NLs in TLC perform the third mission well, then the NLs retain and enhance their own R&D capabilities. These enhanced capabilities are expected to contribute to an accelerated national innovation rate that speeds up the technological and economic development of the TLC (L. Kim, 1980; L. Kim, 1997; K. Lee & Lim, 2001). The performance of the national laboratories in technological latecomer countries must

⁵This allows them, for example, to provide incentives for researchers who are performing well in current R&D projects to continue to do so (personal conversation with Dr. Kwan Sitathani, National Electronics and Computer Technology Center, Thailand).

therefore be defined multi-dimensionally, for success at one mission may compromise another.

2.1.1 Mission 1: Adopt and Adapt

The national laboratories (NLs) in technological latecomer countries (TLCs) are an essential, exogenous component of the product development process of the local technology users (LTUs). The LTUs sequentially engage in idea generation, knowledge sourcing, R&D activity and commercialization (see figure 2.1), in a manner that has been described extensively in the new product development literature (R. G. Cooper & Kleinschmidt, 1986; R. G. Cooper, 1994; Ulrich & Eppinger, 1995). At each stage, they also respectively absorb new ideas, new knowledge and new technologies from external sources, in the manner described by H. Kim & Park, 2010. The national laboratories frequently act as an external source of these ideas, this knowledge and these technologies (W. M. Cohen *et al.*, 2002), and the technology transfer literature suggests that they can flow from the NLs to the LTUs in at least 17 ways (see appendix A). The national laboratories also serve as “a domestic base of good scientists that can provide the basis for breaking into the international networks where new technologies are being originated” (Mazzoleni & Nelson, 2007). Thus the NLs can act as a channel for LTUs to gain access to cutting-edge technology from international sources (Hemmert, 2004). However, to fulfill mission 1, the NLs in TLCs must develop technology that fits local requirements (Arnold *et al.*, 1998) and can be absorbed by the LTUs (Intarakumnerd *et al.*, 2002). The NLs integrate ideas, knowledge and technologies, and customize it for the needs of the LTUs prior to transfer (P. L. Chang & Hsu, 1998; K. Lee

& Lim, 2001). The LTUs can develop radical/breakthrough innovations (Fey & Birkinshaw, 2005) or improve their existing product lines incrementally, if they have the ability to absorb ideas, knowledge and technologies from external sources (Intarakumnerd *et al.*, 2002; P. L. Chang & Hsu, 1998; K. Lee & Lim, 2001).

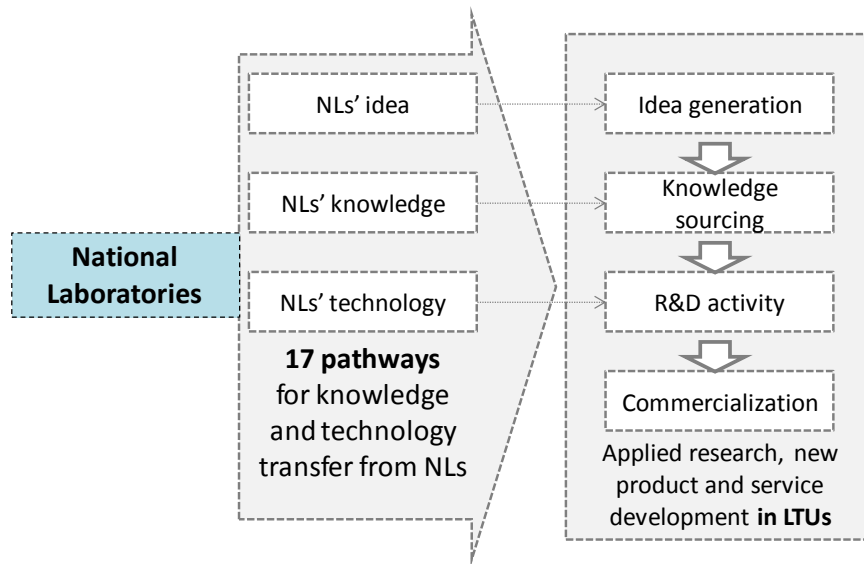


Figure 2.1: Integrating NLs with the innovation process of LTUs (adapted from H. Kim & Park, 2010)

A variety of successful cases of adoption and adaptation by NLs have been discussed in the literature on national innovation systems (Freeman, 1992; Arnold *et al.*, 1998; Lundvall, 1992a; Mazzoleni & Nelson, 2007). In these successful cases, the NLs usually started to build their technological capabilities via assimilation and adaptation of foreign technology. They subsequently developed internal technological capabilities in designing and engineering that were considered a good fit with the technological demands of local industries, whose firms had developed the capabilities that were required to absorb the

technologies from the NLs (Intarakumnerd *et al.*, 2002; P. L. Chang & Hsu, 1998; K. Lee & Lim, 2001). For example, the Korean Institute of Science and Technology (KIST), established in 1966, was the result of collaboration between Korean national government and the Battelle Institute in the USA. KIST activities were aimed to ensure that government research projects can support the demands of local industries such as shipbuilding, steel and machinery industry (Dong-Won & Leslie, 1998; Mazzoleni & Nelson, 2007). A similar strategy was presented in the semiconductor industry in Taiwan. During the 1970s and 1980s, Taiwan's Industrial Technology Research Institute (ITRI) played a critical role in promoting technological collaboration with U.S. firms to adopt advanced technological knowledge from them and subsequently develop local technological capabilities in designing and engineering (P. L. Chang & Hsu, 1998). The Brazilian Agricultural Research Corporation (EMBRAPA) was established in 1972 to coordinate R&D activities and develop linkages between Brazilian research centers and foreign research centers. R&D activities under EMBRAPA were aimed at adapting the research results from collaboration at national level to match the local production system (Mazzoleni & Nelson, 2007). Biodiesel technological development is an example of the successful R&D collaboration under EMBRAPA (Nass *et al.*, 2007).

2.1.2 Mission 2: Technology Commercialization

Based on the technology transfer literature, ten out of the 17 pathways through which knowledge and technology transfer out of NLs by the means discussed in mission 1, can be channels through which the NLs can commercialize their knowledge and technologies.

According to the technology transfer literature, commercialization can occur prior to or after conducting their R&D activities (see appendix A).

Prior to conducting R&D activities, the NLs are likely to gain revenue from

- contract research (J. Lee & Win, 2004);
- joint research between the NLs and LTUs (Zucker *et al.*, 2002; Kulve & Smit, 2003; J. Lee & Win, 2004; Liu & Jiang, 2001); or
- cooperative R&D between NLs and LTUs (Rogers *et al.*, 2001; Carayannis & Gover, 2002; Agrawal, 2002; del Campo *et al.*, 1999; Guan *et al.*, 2006; Liu & Jiang, 2001).

The channels through which R&D organizations can commercialize their knowledge and technology *after conducting their research and development* include

- technology licensing (Rogers *et al.*, 2001; Petroni & Verbano, 2000; King & Nowack, 2003; Feller *et al.*, 2002; Agrawal, 2002; Feldman *et al.*, 2002; Shane, 2002; Chapple *et al.*, 2005; J. Lee & Win, 2004; Siegel, 2004; Bercovitz, 2006; del Campo *et al.*, 1999);
- consultancy services (Agrawal, 2002; Guan *et al.*, 2006);
- services pertaining to seminars and conferences (Agrawal, 2002; J. Lee & Win, 2004);
- training services (Hong, 1994; Guan *et al.*, 2006);
- services pertaining to technology and business incubators (Phillips, 2002; Lofsten & Lindelof, 2003; Markman *et al.*, 2005); and

- services in technology parks, science parks and other R&D facilities (Lofsten & Lindelof, 2003; Petroni & Verbano, 2000; Markman *et al.*, 2005; Liu & Jiang, 2001; Feller *et al.*, 2002).

In technology latecomer countries, commercialization acts as an alternative pathway through which NLs can benefit from technology that they have developed but that the LTUs will not develop.

2.1.3 Mission 3: Retain and Enhance National Competitiveness

The national laboratories (NLs) have served as a backbone to provide advanced research and development for the future needs of local technology users (LTUs) (L. Kim, 1997). On the one hand, the NLs in TLCs typically set up R&D projects to solve current problems in existing technology areas (as discussed in mission 1). On the other hand, the NLs in TLCs need to initiate advanced R&D projects to prepare for future problems in new technology areas, which tend to have a high risk of failure but provide a high economic impact. The NLs need to initiate highly advanced R&D projects that are focused on elevating the long-term technological capability of LTUs (L. Kim, 1997, pp. 50-51). This approach allows NLs in TLCs to retain and enhance national competitiveness in science and technology.

The level of technological capability⁶ of LTUs in TLCs tends to be at the level of technological imitators. LTUs in TLCs tend to acquire mature technology from abroad, and then implement it in their production process (L. Kim, 1980). At this stage, NLs may help LTUs in executing the acquisition, assimilation and improvement of the mature technology from the advanced technological countries (P. L. Chang & Hsu, 1998). ITRI, for example, acquired medium-scale integrated (MSI) circuit process technology from abroad, and assimilated it to produce products that were differentiated from the foreign products that they were imitating.

Next, to sustain their competitiveness, LTUs need to make a few internal efforts induce technological change in both products and processes. However, LTUs in TLCs tend to lack the requisite technological capabilities and market incentives to develop their own technologies (L. Kim, 1980, p. 258). The LTUs also have inadequate advanced industrial research experience and perform only incremental and reactive learning (L. Kim, 1997, p. 85). At that stage of national economic development, the NLs have to take on the role of continuously accumulating internal technological capabilities that can help the LTUs continuously improve their products, process and services, or perhaps even generate radical innovation (L. Kim, 1997; P. L. Chang & Hsu, 1998). ITRI, for example, built up technological capabilities to develop large-scale integrated (LSI) circuits, very large-scale integrated (VLSI) circuits, and ultra-large-scale integrated (ULSI) circuits to serve future

⁶Technological capability is determined by a function of prior knowledge and technological effort in research and development (L. Kim, 1997). Technological capability is generated as a by-product of a research and development activities particularly when advanced technological knowledge is less explicit, less codified, and more difficult to assimilate. According to L. Kim (1997, p.93), "the more difficult learning is, the more knowledge has to have been accumulated via R&D for effective learning to occur".

demands of their targeted industry after the successful adoption of medium-scale integration (MSI) (P. L. Chang & Hsu, 1998).

As a technology producer within TLCs, the NLs must also take on an important role in helping LTUs retain and enhance their competitiveness, particularly in industries or technologies that have been targeted for development by their national governments (L. Kim, 1997; P. L. Chang & Hsu, 1998). NLs typically help LTUs improve their technological capability by sponsoring and conducting research and development projects within the NLs and transferring them output of these projects to the LTUs.

2.1.4 Summary of Section

Figure 2.2 summarizes the findings of this section. The NLs' *first mission* as a technology adopter drives them to focus on adopting technological knowledge from abroad and adapting it to the LTUs' requirements *for the benefit of the LTUs*. NLs transfer many of the processes, products and services they have developed to the LTUs via 17 known pathways (see appendix A). *The second mission*, which is aimed at the commercialization of technology, drives the NLs to focus on generating revenue from the technologies that they have developed *for the benefit of their own organizations*. The NLs can commercialize these technologies and transfer them to the LTUs via 10 pathways. The NLs' *third mission* as a technology producer drives the NLs to build up their internal capabilities in research and development for retaining and sustaining national competitiveness in science and technology, i.e. the national laboratories are working *for the future of the country*. This knowledge also tends to be retained and flow within the

NLs. It is embedded within individual researchers and project groups who have performed the abovementioned R&D, and it acts as a form of prior knowledge that can be used in future projects.

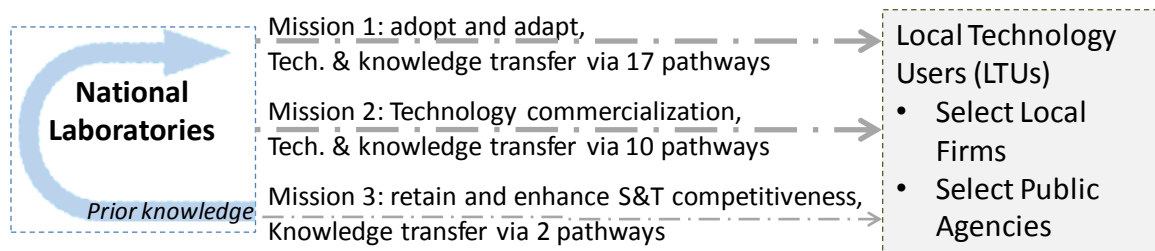


Figure 2.2: The pathways for knowledge and technology flow out of NLs for each mission

To succeed in the three missions, the NLs need to deliver many successful R&D projects. They need to establish and strengthen their internal technological capability by setting up internal research and development projects. Internal R&D project groups are considered as a source of internal knowledge that allows NLs to build up their internal absorptive capacity (W. M. Cohen & Levinthal, 1990). However, the NLs also need to engage with external sources of knowledge for acquiring new knowledge. The following section will discuss the internal and external sources of knowledge and the pathways through which NLs in TLCs can obtain knowledge.

2.2 EXTERNAL AND INTERNAL KNOWLEDGE FOR NATIONAL LABORATORIES IN TECHNOLOGY LATECOMER COUNTRIES⁷

The sources of knowledge that are available to a project group at the national laboratories can come from inside the project group that is working on the project or from external sources of knowledge. The external sources include other project groups inside NLs, as well as other institutions both inside and outside national innovation system (NIS). There are two main pathways for obtaining external knowledge: contextual learning activities (CLAs) and vicarious learning activities (VLAs) (Bresman, 2010). The internal knowledge of a project group can be generated through grafting the prior experience of individual members of a project group (Huber, 1991) or from relevant knowledge that the project group has accumulated prior to the inception of an ongoing project (Nemanich *et al.*, 2010). It can also be created by deliberate project internal learning activities that take place while the project is ongoing (e.g., Adler & Clark, 1991; Bohn, 1994; Lapré *et al.*, 2000, Edmondson *et al.*, 2003). Integrating knowledge that flows into the project group with knowledge from internal sources allows the project group to create new technological knowledge, new technology, or innovative products and services (W. M. Cohen & Levinthal, 1990).

⁷ In this section of the literature review, I look at the external sources and internal sources of knowledge for research and development projects at national laboratories (NLs) in technology latecomer countries (TLCs). I focus on the four important sources of external knowledge for the NLs in TLCs, which I describe in detail to provide a better understanding of the sources of knowledge for the NLs in TLCs. I also review the pathways for obtaining external knowledge and mechanisms for generating internal knowledge for the NLs in TLCs. Most of the articles that are reviewed in this section come from the literature on technology transfer and organizational learning. However, I also draw on the literature on national innovation systems, Open Innovation and new product development.

2.2.1 Sources of External Knowledge

External knowledge is knowledge that is not created within the project groups. It can flow into project groups within the NLs from other projects inside the NLs, from external sources that are outside NLs but inside national innovation system of TLCs, and from sources that are outside national innovation system of TLCs.

2.2.1.1 Other Projects inside National Laboratories in Technology Latecomer

Countries

Other projects within the national laboratories can serve as a source of knowledge, if project groups within the NLs engage in learning activities that span organizational boundaries (Ancona & Caldwell, 1992; Haas & Hansen, 2005; Haas & Hansen, 2007). Project members may search for technical knowledge of other projects from organization databases (Haas & Hansen, 2005; Haas & Hansen, 2007). The project members may also interact with experts of other projects to learn from their experiences (Haas & Hansen, 2005; Haas & Hansen, 2007; Bresman, 2010). Knowledge gains from other projects inside NLs tends to allow project groups save time during their tasks (Haas & Hansen, 2007) and may allow them to integrate technology that fits with customer requirements.

2.2.1.2 Institutions inside the National Innovation Systems of Technology Latecomer

Countries

Knowledge can flow into project groups within the NLs from other institutions that are outside the NLs but within their national innovation systems. These sources include local

universities that provide local scientific and technological knowledge, as well as the LTUs, which provide feedback on the technologies that the NLs deliver and information about the use environment (von Hippel, 1988) of these technologies.

- **2.2.1.2.1 Technological Knowledge from Domestic Sources**

A variety of empirical studies have shown that local universities play a preeminent role in technological development within the national innovation system (NIS) (Dahlman & Frischtak, 1990; Geisler, 1995; Gelsing, 1992; Hou & Gee, 1993; J. M. Katz & Bercovich, 1993; L. Kim, 1993; Mowery & Sampat, 2005; Teubal, 1993; Faulkner & Senker, 1995; Etzkowitz, 2003). Pavitt, 1998 (p. 796) suggests that local universities provide 1) useful knowledge inputs that can lead directly to prospected applications; 2) engineering design tools and techniques that can help in designing and testing of complex technological systems; and 3) trained scientists and engineers who can apply their knowledge beyond academic research and can help to access to academic community via their informal network. NLs also can access to technological knowledge from local universities via these channels.

In some countries, governments may establish national laboratories to bridge the gap between academic research in university and industrial research in industry (Encarnaç o, 2007; KIST, 2011; Fraunhofer, 2011). Academic research in local universities tends to be less relevant to the requirements of industry (*i.e.*, Intarakumnerd *et al.*, 2002). Also, some research programs that are high risk tend to require resources on a large scale; need long-term commitment; or demand interdisciplinary R&D projects. Such programs need to be

initiated by the national institutes (KIST, 2011). Government may encourage collaboration between local universities and the NLs, which may act as a pathway for knowledge flow from local universities into the NLs.

- **2.2.1.2.2 User Knowledge from Local Technology Users**

LTUs tend to be a critical source of knowledge for research and development projects at NLs. LTUs provide feedback on the technologies that the NLs deliver and information about the use environment (von Hippel, 1988) of these technologies. In an NIS, Lundvall argues “the relationships between public research institutes that produce basic and applied research and industry as a user of science may be fruitfully analyzed as one specific form of user-producer interaction” (Lundvall, 2010, p. 51). The interaction between users and producers tend to create product innovations (Lundvall, 2010, p. 50). It also facilitates the flow of information for the producer (the NLs). There are two types of knowledge in this interaction: technical opportunities and user needs (Lundvall, 1992b). Therefore, LTUs are considered a critical source of external knowledge for NLs.

2.2.1.3 Institutions outside the National Innovation Systems of Technology Latecomer Countries

Knowledge can flow into project groups within the NLs from sources outside their national innovation systems include foreign universities, national laboratories in other countries and multinational corporations (MNCs). At the country level, a latecomer country can access the international sources of technological knowledge by engaging in international technology transfer. The pathways for international technology transfer into

a technological latecomer country include foreign direct investment (FDI) by multinational corporations (MNCs) (Hoekman *et al.*, 2005; Simango, 2000; Guan *et al.*, 2006; King & Nowack, 2003; Farhang, 1997), movement of people from MNCs to local industries or from one country to another (Hoekman *et al.*, 2005; Ploykitikoon & Daim, 2010; Chen & Sun, 2000; Gil *et al.*, 2003), import of equipment and instruments (Hoekman *et al.*, 2005) and technology licensing (King & Nowack, 2003; Salicrup & Fedorkova, 2006; Hoekman *et al.*, 2005).

Moving people from one entity to another tends to be a major channel through which NLTs in TLCs can gain access to advanced technological knowledge from abroad (Utterback, 1975; Mazzoleni & Nelson, 2007). Hiring people who have studied or worked abroad or worked within the country at a foreign-owned corporation, even for a limited period of time, enables knowledge that was created outside the country to flow into technological latecomer countries (Hoekman *et al.*, 2005; Utterback, 1975; Mazzoleni & Nelson, 2007). In particular, moving people from abroad to technological latecomer countries has been considered a crucial pathway for international technology transfer (Ploykitikoon & Daim, 2010). For example, the government of Taiwan succeeded in promoting the repatriation of scientists and engineers. This pathway helped Taiwan succeed in developing its electronics and semiconductor industries. More recently, the government of India has instituted a policy that promotes the temporary return of expatriates and encourages the returnees to conduct local research and develop local businesses (Hoekman *et al.*, 2005). People with experience in working or studying abroad also enable knowledge transfer from advanced technological countries to national

laboratories (Utterback, 1975; Mazzoleni & Nelson, 2007). Thus, international sources of knowledge can be considered as a critical source of external knowledge for NLS.

2.2.2 Sources of Internal Knowledge

Knowledge that is relevant to the execution of a particular project may already be available to the project group at the outset of the project that it intends to pursue (Haas & Hansen, 2005; Haas & Hansen, 2007). This knowledge is henceforth classified as static because the project group can utilize this knowledge without doing anything during the execution of the project. Static knowledge can come from external experience that the members of the project group have accumulated prior to joining the group (Huber, 1991).⁸ Alternatively, it could have been created by the project group prior to the inception of the project that the group plans to pursue (Nemanich *et al.*, 2010). By contrast, internal knowledge that is classified as dynamic is created through deliberate learning efforts that take place while the project is ongoing (e.g., Adler & Clark, 1991; Bohn, 1994; Lapré *et al.*, 2000; Edmondson *et al.*, 2003). These activities allow the project group to renew its stock of knowledge, which may otherwise become obsolete (Nemanich *et al.*, 2010).

⁸Huber (1991) talks about experience that has been accumulated prior to joining an organization. Such an organization can consist of many project teams. Huber's conclusions should apply to project teams within an organization that consists of many such teams.

2.2.3 Pathways for Obtaining External Knowledge

Researchers tend to exchange knowledge (some of which may even be proprietary) across organizational boundaries (e.g., Allen, 1977; Kreiner & Schultz, 1993; von Hippel, 1987; Bouty, 2000, p. 50). Bouty, 2000, (p. 50) states that researchers “may meet at conferences or annual meetings or are classmates. They know each other, and they belong to networks. They call on each other for assistance in their daily work, when they confront an issue they are unsure about or cannot work out.” Researchers activate their networks to exchange information and services with their colleagues, including those that are employed by their direct competitors (von Hippel, 1987; Bouty, 2000). Furthermore, Bouty, 2000, states that past research has proven that these informal interactions across organizational boundaries may constitute major learning processes that are of great consequence for innovation. For example, Allen, 1977, found that “about 40 percent of the messages resulting in ideas considered during the course of R&D projects and 40 percent of the ideas considered as potential solutions stemmed from personal contacts outside the scientists' own firms,” and these “resources also flow out of firms through these exchanges. Moreover, these exchanges are purely interpersonal (between individuals), ad hoc, and independent of organizational structure, policy, and formal collaborations” (Allen, 1977, pp. 45-64, 148, 155, 223, 225; Bouty, 2000).

In my study, knowledge from external sources such as the ones mentioned above can flow into organizations via two main pathways: contextual learning activities (CLAs) and vicarious learning activities (VLAs) (Bresman, 2010).

2.2.3.1 Contextual Learning Activities (CLAs) or Searching

Contextual learning (Allen, 1977; Ancona & Caldwell, 1992; Hansen, 1999; Bresman, 2010), which (Ancona & Caldwell, 1992) originally named searching and scouting, can occur in two forms: scanning and focused search. Scanning (Huber, 1991) or broad search (Laursen & Salter, 2006) refers to wide-range sensing of the organization's external environment (Huber, 1991). Focused search (Huber, 1991) or deep search (Laursen & Salter, 2006) occurs when organizational units or their members actively search in a narrow segment of the organization's internal or external environment, often in response to actual or suspected problems or opportunities (Huber, 1991).

At the project level, contextual learning activities (Bresman, 2010) help a group learn about its context from external sources of knowledge. Contextual learning activities include scanning the environment for information and ideas about competitors, customers, and technological trends. They allow group members “to ensure that they are staying abreast with the competition, that they are working on a product that customers value, and they are not about to be leapfrogged by new technologies” (Bresman, 2010, p. 86). Group members scan the environment to keep track of its dynamic context and to adjust the group’s practices to ensure they align with the context as it changes over time. Contextual learning activities tend to involve declarative knowledge⁹, which is explicit

⁹ The differences between declarative and procedural knowledge have been addressed in the literature: (e.g., M. D. Cohen & Bacdayan, 1994; Moorman & Miner, 1998; Edmondson et al., 2003; Bresman, 2010): Declarative knowledge is about facts: 1) it is explicit; 2) can be accessed consciously; 3) it is easy to articulate and store; and 4) it is easy to apply across a variety of tasks. Procedural knowledge is about how

and about facts. Thus, they are easier to communicate and record than vicarious learning activities (Bresman, 2010), which tend to be more tacit and procedural (Edmondson *et al.*, 2003). CLAs enable group members to enhance their awareness of current events that are taking place outside their organization. These events may pertain to new technology, the organization's competitors and the market space in which the organization participates. Awareness of these events may enter the organization via conferences and publications.

2.2.3.1 Vicarious Learning Activities (VLAs)

Vicarious learning acquires second-hand experience (Argote & Ingram, 2000; Edmondson *et al.*, 2003; Darr *et al.*, 1995; Epple *et al.*, 1991; Bresman, 2005; Bresman, 2010). Organizations engage in VLAs in an attempt to not just inform themselves about whether particular strategies, practices and technologies exist within other organizations. They are also interested in the processes that these organizations deploy to implement these strategies and practices, as well as to develop technology. For example, an organization is engaged in vicarious learning activities if it searches for information not just about what competitors are doing, but also how they are doing it (Porter, 1980; Sammon *et al.*, 1984; Fuld, 1988; Gilad & Gilad, 1988; cited by Huber, 1991, p. 96). Organizations can gain access to second-hand experiences via the same channels through which they engage in contextual learning: e.g. consultants, professional meetings, trade shows, publications, vendors, and suppliers. However, the knowledge that they obtain

things are done: 1) It is tacit, 2) it tends to be accessed unconsciously, 3) it tends to be difficult to articulate and store, and 4) it is likely to be difficult to apply across tasks.

tends to be tacit and procedural rather than explicit and declarative. In addition, Huber, 1991, has suggested that networks of professionals in specific technology areas (see, for example, Almeida *et al.*, 2003; Oliver & Liebeskind, 1997; Almeida & Kogut, 1997; Rosenkopf & Tushman, 1998) can serve as a channel for vicarious learning activities that facilitates the inflow of knowledge in less competitive environments.

At the project level, vicarious learning activities constitute a set of group learning activities through which a group learns about its ongoing project from experienced outsiders. Vicarious learning activities can help group members “avoid repeating mistakes and reinventing practices, and skip unnecessary steps; identify important practices and procedures; and learn how to implement them” (Bresman, 2010, p. 84). A group may learn from the lessons others have learned by “inviting them to discuss past mistakes; reflecting experience of others on what has worked in the past; extracting lessons about the task; observing the work of others; and talking to others about way to improve the work process” (Bresman, 2005, p. 84). Vicarious learning activities involve both declarative (explicit) and procedural (tacit) knowledge; thus they require active engagement between knowledge providers and receivers. Success at vicarious learning activities can be achieved by “an iterative process of intense interpersonal interaction involving discussion, observation, and problem solving” (Bresman, 2010, p. 86). Vicarious learning activities also can be implemented by setting up advisory group or by exchanging experiences with other research groups who have had similar experiences (Bresman, 2010).

2.2.4 Obtaining Internal Knowledge

Internal knowledge can come from prior experience of individual members of a project group (Huber, 1991) or from relevant knowledge that the project group has accumulated prior to the inception of an ongoing project (Nemanich *et al.*, 2010). It can also be created by deliberate project-internal learning activities that take place while the project is ongoing (e.g., Adler & Clark, 1991; Bohn, 1994; Lapré *et al.*, 2000; Edmondson *et al.*, 2003).

2.2.4.1 Grafting Prior Experience

Grafting on new members is a process through which an organization can rapidly gain new knowledge that has not been previously available within the organization. It primarily consists of moving people with relevant knowledge, experience and expertise from one organization or project group to another (Huber, 1991). An organization may acquire new knowledge from a strategic alliance partner (Mowery *et al.*, 1996; Rosenkopf & Almeida, 2003; Madhavaram & McDonald, 2004; Nag *et al.*, 2007; Segelod, 2001; Lyles & Salk, 1996) by having people from the strategic alliance partner work jointly with people from its organization within the same project group. This practice enables the socialization processes that are required for knowledge transfer or the creation of new knowledge (Nonaka, 1994). Successful grafting can also occur by hiring additional scientists and engineers (Zucker *et al.*, 1998; Almeida & Kogut, 1999) from abroad (Antal & Walker, 2011; Hoekman *et al.*, 2005; Ploykitikoon & Daim, 2010; Chen & Sun, 2000; Gil *et al.*, 2003), from inside the country but outside the organization

(Huber, 1991) or from within the organization but outside the project group (Haas & Hansen, 2005) and integrating them into the project group (see figure 1.1).

2.2.4.2 Prior Knowledge

Prior knowledge is an internal factor that tends to impact the relationship between knowledge inflows and organizational performance (W. M. Cohen & Levinthal, 1990; Todorova & Durisin, 2007; Szulanski, 1996; Simonin, 1999; Matusik, 2002; De Clercq & Dimov, 2008). Prior knowledge includes “basic skills, a shared language, and knowledge of the most recent scientific or technological developments in a given field” (W. M. Cohen & Levinthal, 1990, p. 131). Prior knowledge within an organization enables the assimilation and exploitation of external knowledge, especially if some portion of that prior knowledge is closely related to the new external knowledge to be assimilated (W. M. Cohen & Levinthal, 1990).

An individual’s prior knowledge comes from all the learning that he/she has done in the past. “Learning performance is greatest when the object of learning is related to what is already known” (W. M. Cohen & Levinthal, 1990, p. 131), because it enhances the individual’s ability to absorb new knowledge. An increase in absorptive capacity over one time period will permit the individual to absorb more knowledge in subsequent time periods. If multiple individuals develop absorptive capacity in their respective areas of expertise, and these areas of expertise are related to the mission of the organization, then the organization’s capacity to absorb useful knowledge increases. The organization should consequently be able to increasingly exploit critical external knowledge as it

becomes available (W. M. Cohen & Levinthal, 1990, pp. 135- 136), but only if the organization enables the individuals that work within it to engage in the socialization processes that are required for successful knowledge creation and knowledge transfer within the organization (Nonaka, 1994).

At project the level, prior knowledge has the tendency to affect the relationship between knowledge inflow and project performance (Griffith & Sawyer, 2009; Nemanich *et al.*, 2010). It enhances the combinative capabilities (Kogut & Zander, 1992) of the project group, which can subsequently reorganize knowledge from various sources, be they external or internal, to achieve better results. Nemanich *et al.*, 2010 also contend that prior knowledge facilitates a project group's ability to replicate actions that have produced successful results in the past. However, these authors present no empirical evidence that backs up this proposition.

2.2.4.3 Project-Internal Learning Activities (PILAs)

Project internal learning activities (PILAs) help project group members learn from experience as they execute their own projects (Edmondson, 1999; S. Wong, 2004; Bresman, 2010). The activities typically include “asking questions, seeking feedback, sharing information, experimenting, and talking about errors” (Bresman, 2010, p. 82). PILAs also play an important role for project members to absorb external knowledge that

they have gained from technology gatekeepers.¹⁰ W. M. Cohen & Levinthal, 1990, have argued that not all members of a project group need to interact with external entities at the group level. Instead, the project group may interact with its environment via a technology gatekeeper, who takes a lead role in the evaluation and assimilation of external knowledge. PILAs allow the gatekeeper to share knowledge inflows with their project members.

2.2.5 Summary of Section

Figure 2.3 represents the conclusion of this section. The literature review presents four main sources of external knowledge inflow into research and development projects of NLs. The sources of external knowledge include existing technological knowledge from other projects inside NLs, technological knowledge from local universities, user knowledge from LTUs, and technological knowledge from abroad. The knowledge from these four sources can flow into R&D projects at NLs in TLCs via the three strategic pathways: grafting, vicarious learning activities, and contextual learning activities. In this study, grafting people is considered a mechanism that brings knowledge from external sources into the project group prior to the outset of a project. It is treated as an internal source of knowledge while the project is ongoing.

¹⁰Technology gatekeepers are employees that interact extensively with individuals and organizations outside their own (Allen, 1971; Tushman & Katz, 1980; R. Katz & Allen, 1982). They consequently bring technology into an organization from the outside. They have a reputation for technical competence in a particular field; they read the journals in the field; they have many external connections; and they are frequently promoted to first level supervisory positions. Gatekeepers of a particular technology tend to be organized in networks. They go to the same conferences, and they join the same professional societies. Gatekeepers of different technologies within the same organization also engage with each other, increasing their effectiveness in coupling their organization to the outside world (Allen, 1977, Ch. 6).

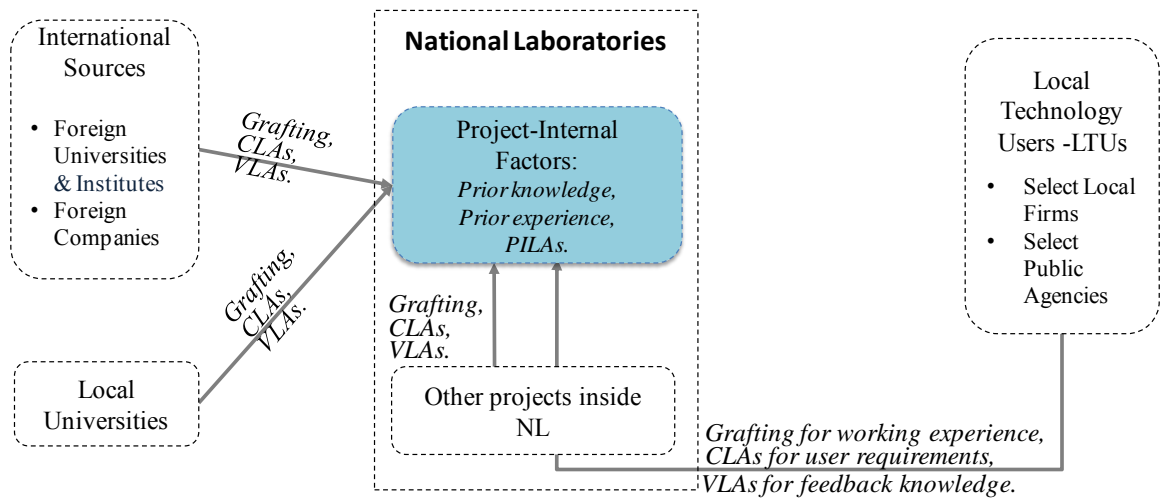


Figure 2.3: Knowledge inflow surrounding national laboratories. (integrated from Utterback, 1975; Mazzoleni & Nelson, 2007; Hoekman *et al.*, 2005; Encarnaç o, 2007; Lundvall, 2010; Ancona & Caldwell, 1992).

2.2.6 Primary Research Gap

The literature that has been reviewed so far has identified the following primary research gap. Currently, to the best of my knowledge, *no quantitative study on the impact of the four main sources of external knowledge and of the three main sources of internal knowledge on the performance of NLs has ever been done* (**Primary Research Gap**). I intend to address this primary gap in the academic literature in my dissertation by investigating the impact of knowledge inflows on performance of NLs in TLCs.

To clarify the issues regarding the primary research gap, I review the literature concerning the impact of managing knowledge inflows into research and development

organizations sections 2.3 and 2.4. By doing so, I identify various research gaps that are subordinate to the primary research gap.

2.3 THE IMPACT OF MANAGING KNOWLEDGE INFLOWS INTO R&D ORGANIZATIONS

In this section of the literature review, I look at some broadly based issues pertaining to knowledge inflow in research and product development. I focus on how managing knowledge inflow impacts the performance of research organizations and development organizations, both at the organization level and at the project level. *Managing knowledge inflows* consists of deciding which external source of knowledge to tap as well as identifying the best pathway for knowledge inflow into the national laboratories and the various project groups that actually works on the R&D projects.¹¹

2.3.1 Open Innovation

Two studies by Chesbrough (Chesbrough, 2003; Chesbrough *et al.*, 2006) (which utilize the case study research method) suggest that companies should consider managing knowledge inflows not only for obtaining new ideas, knowledge or technology, but also for commercializing them through a process of managing knowledge outflow (West &

¹¹ The findings from this section will allow me to analyze in more detail the primary research gap that has been identified in section 2.2.6. Most of the articles that are reviewed in this section come from the literature on organization learning and absorptive capacity. However, I also draw on the literature on Open Innovation and new product development.

Bogers, 2011). The process through which this is done is known as Open Innovation. Chesbrough *et al.* (2006) defines “Open Innovation” as the use of purposive inflows and outflows of knowledge to accelerate internal innovation, and expand the markets for external use of innovation, respectively.

Open Innovation is based on the principle that no company employs *all* talented people needed to gain competitive advantage, but that valuable knowledge also resides in external sources of knowledge. Open Innovation is a paradigm that assumes that firms can and should use external ideas as well as internal ideas, and internal and external paths to market, as they look to advance their technology (Chesbrough *et al.*, 2006). Companies need to systematically identify and acquire external knowledge in order to *accelerate internal innovation*. This process is known as *Inbound Open Innovation* (Chesbrough *et al.*, 2006). Furthermore, Chesbrough *et al.* (2006) suggests a similar approach to exploit internally generated knowledge. In addition to the "normal" way of commercializing knowledge through the company's own products and services. He suggests the companies should also target at *generating value from other companies' use* of the company's knowledge. This process is known as *Outbound Open Innovation*.

2.3.2 Multi-Dimensional Impact

Much of the academic literature that addresses how knowledge is obtained from external sources and transferred across organizational boundaries (*e.g.*, Ancona & Caldwell, 1992; Haas & Hansen, 2007; Laursen & Salter, 2006; Chiang & Hung, 2010) suggests that said knowledge can have a significant, multi-dimensional impact on the performance of the

organizations into which it flows. Successfully managing knowledge inflow can shorten development time and decrease the costs of developing an innovation (Chesbrough, 2003; Backer, 2008) (*dimension -1*). Knowledge inflows also tend to bring new innovative ideas into organizations (Chesbrough, 2003; Piller & Walcher, 2006; Hill & Birkinshaw, 2008). Systematically identifying and acquiring external knowledge, which can be combined with internal knowledge, is likely to improve the innovative performances of organizations when they try to develop advanced products or engage in process innovation (*dimension -2*) (Gassmann *et al.*, 2006; Gassmann, 2006; McAdam *et al.*, 2006; Reichstein & Salter, 2006; Carson, 2007; Harryson *et al.*, 2008; West & Bogers, 2011¹²).

Organizations should also be able to gain additional benefits from commercializing technology that they have developed internally (*dimension -3*) (Zuniga & Guellec, 2009; Lichtenthaler, 2008; Lichtenthaler, 2006a; West & Bogers, 2011). The literature on Open Innovation discusses the three channels by which a company can gain benefits from the outflow of knowledge: divestment of a company's business units, IP management, and inter-organizational collaboration (e.g., Lichtenthaler, 2005; Chesbrough & Garman, 2009). The divestment of a business unit involves the sale and transfer of *all* of the

¹²West & Bogers, 2011, identified three plus one major steps for profiting from external innovations. **Obtaining innovations** include search, sourcing, enabling, incentivizing and contracting. Initially, we separated the search for external innovations from their acquisition, but we eventually concluded that for much of the sample, it was impossible to separate these processes and roles. **Integrating innovations**, including factors that enable integration, those that act as barriers to integration, and those that explain how that activity changes (and is changed by) the organization and its competencies. **Commercializing innovations** is often implied for Open Innovation research, but an explicit part of conventional models of industrial R&D. To this three-step linear model West & Bogers (2011) added a fourth category of **non-recursive paths**, which involve reciprocal interactions with co-creation partners. The authors have termed this process a four-phase model of how firms utilize external innovations.

company's relevant knowledge (intellectual property (IP) rights, physical assets and human resource assets) to a spin-off business unit (Lichtenthaler, 2005; Chesbrough, 2002; Chesbrough & Rosenbloom, 2002). IP management includes activities such as licensing out, cross-licensing and IP donation (Elton *et al.*, 2002; Davis & Harrizon, 2001; Rivette & Kline, 2000), which involves transfer of *some* of the company's relevant knowledge. Inter-organizational collaboration includes strategic alliances, joint ventures, and inter-organizational networks in which the IP rights are *shared* between the partners in the collaboration (Lichtenthaler, 2005).

To date, very few studies that measure the impact of knowledge inflow on the commercialization of technology have been conducted (West & Bogers, 2011). The few studies that have addressed this subject are based on the case study research method, and they have chosen the organizational level as a unit of analysis (Chesbrough, 2003; Dodgson *et al.*, 2006; Cooke, 2005). To date, to the best of my knowledge, the impact of knowledge inflow on revenue generation has not been studied quantitatively (Research Gap RG-1), neither in research and development organizations at NLRs in TLCs nor elsewhere. In addition, the subject has not been investigated at the project level. Finally, I contend that the impact of *managing* knowledge inflow on the commercialization of technology that has been developed inside an organization or a project group has not been studied at all.

2.3.3 Conclusion of this Section

Table 2.1: Performance measures in the existing literature and in my proposal (output variables)

Author(s)	Performance Measures					
	Innova- tiveness	Efficiency	Bidding success	Client's satisfaction	Quantity & quality of codified knowledge	Revenue generated
<i>Performance dimensions at organizational level (based on conceptual framework or case studies)</i>						
Chesbrough, 2003; Backer, 2008; West & Bogers, 2011	YES	YES				YES
Gassmann, 2006; McAdam <i>et al.</i> , 2006; Harryson <i>et al.</i> , 2008	YES					
Zuniga & Guellec, 2009; Lichtenthaler, 2008; Lichtenthaler, 2006a						YES
My dissertation: NLS in TLCs				YES	YES	YES
<i>Performance dimensions at organizational level (based on large-scale empirical data)</i>						
Laursen & Salter, 2006	YES					
Chiang & Hung, 2010	YES					
<i>Performance dimensions at project level (based on large-scale empirical data)</i>						
Ancona & Caldwell, 1992	YES	YES				
S. Wong, 2004	YES	YES				
Haas & Hansen, 2005			YES			
Haas & Hansen, 2007		YES		YES		
Bresman, 2010	YES	YES				
My dissertation: NLS in TLCs				YES	YES	YES

Note: The solid columns refer to the measures that are the primary concern of NLS in TLCs.

Table 2.1 represents the conclusion of this section. It presents the performance metrics that measure the impact of managing knowledge inflows at the organization level and the project level. In the research streams of Open Innovation, organizational learning and NPSD, knowledge inflows contribute to 1) innovativeness in products and services and 2) the efficiency of the innovation process. However, knowledge inflows also help

organizations generate 3) innovations that satisfies the client; 4) codified knowledge for future uses; and 5) revenue from commercializing technology. Based on the literature review in this section, the last three dimensions, which are of critical importance to the three fundamental missions of NLTs in TLCs, are the focus of the large-scale empirical research that I conduct as part of my dissertation.

Table 2.2: Main literature pertaining to managing knowledge inflows at project level

Author(s)	Types of projects	Internal knowledge (internal project factors)	External knowledge (experience-sources)	Pathways of Knowledge inflows	Performance (dimensions)	Results
Ancona & Caldwell, 1992	NPD projects	None	General knowledge outside project	CLAs	<ul style="list-style-type: none"> ▪ Innovativeness ▪ Efficiency 	<ul style="list-style-type: none"> ▪ The CLAs impede group projects to achieve both group innovativeness and efficiency
S. Wong, 2004	Diversified teams	PILAs	General knowledge outside project	CLAs	<ul style="list-style-type: none"> ▪ Innovativeness ▪ Efficiency 	<ul style="list-style-type: none"> ▪ The CLAs promote group innovativeness ▪ The PILAs promote group efficiency ▪ The CLAs impede PILAs for achieving group efficiency (-)
Bresman, 2010	In-sourcing projects	PILAs	General knowledge outside organization	CLAs VLAs	<ul style="list-style-type: none"> ▪ Innovativeness ▪ Efficiency 	<ul style="list-style-type: none"> ▪ CLA and VLA support group innovativeness and efficiency ▪ PILAs complement VLA to enhance group performance (+) ▪ When group performs VLA, lacking PILAs can hurt group performance
Haas & Hansen, 2005	Consulting projects	Prior experience in task	Knowledge outside project, but inside organization	<ul style="list-style-type: none"> ▪ CLAs from internal codified knowledge ▪ VLAs from internal personal knowledge 	Binary numbers (0= not success, 1=success in bidding)	<ul style="list-style-type: none"> ▪ Both CLAs and VLAs (that only new for the team, but not new to the organization) impedes the chance to succeed in projects with high prior experience (-)
Haas & Hansen, 2007	Consulting projects	None	Knowledge outside project, but inside organization	<ul style="list-style-type: none"> ▪ CLAs from internal codified knowledge ▪ VLAs from internal personal knowledge 	<ul style="list-style-type: none"> ▪ Time efficiency ▪ Client's satisfaction ▪ Project competency 	<ul style="list-style-type: none"> ▪ CLAs saves time during the task, but not improves client's satisfaction and project competency ▪ VLAs improve improves client's satisfaction and project competency, but not saves time during the task
Nemanich <i>et al.</i> , 2010	R&D projects	Prior knowledge (#patent)	General knowledge outside organization	Assimilation ability	Exploitation ability	<ul style="list-style-type: none"> ▪ Assimilation ability is more important to performance in projects with less prior knowledge than in projects with extensive prior knowledge

CLAs = Contextual learning activities; VLAs = Vicarious learning activities; PILAs= Project internal learning activities

2.4 FACTORS THAT IMPACT KNOWLEDGE INFLOWS AT PROJECT LEVEL

In this section of the literature review, I look at some broadly based issues pertaining to knowledge inflows in research and product development. I investigate which factors are important to managing knowledge inflows, and I focus on which organization-internal factors enable or hinder knowledge inflows. The findings from this section will allow me to address research gaps, research questions, and research hypotheses for my dissertation proposal. Most of the articles that are reviewed in this section come from the literature on organizational learning and absorptive capacity.

Table 2.2 presents the findings of the existing literature that addresses how knowledge inflows impact performance at the project level. The impact of knowledge inflows on project performance tends to vary by types of projects, according to internal project factors and by the choice of pathways and sources of knowledge inflows.

2.4.1 Types of Projects

The relationship between knowledge inflows and project performance is impacted by what type of project the project is. For example, the performance of new product development (NPD) projects tends to rely less on knowledge inflows via CLAs than in-sourcing projects and service development projects and manufacturing projects do. As presented in Table 2.2, CLAs tend to have a negative impact on efficiency and innovativeness in new product development project (Ancona & Caldwell, 1992), but they have a positive impact on both efficiency and innovativeness in technology in-sourcing

projects (Bresman, 2010). They have a positive impact on the innovativeness and no significant impact on the efficiency of service development projects and manufacturing projects (S. Wong, 2004).

To date, the impact of knowledge inflows on the performance of research and development projects of NLs in TLCs has not been measured. The literature review in section 2.2 suggests that the performance of NLs in TLCs tend to be highly related to knowledge inflows, particularly those from abroad. However, to date *no empirical study has determined the degree to which the performance of R&D projects at NLs in TLCs relies on knowledge inflows.* (Research Gap RG-1)

2.4.2 Project-Internal Factors

The literature review in sections 2.2.2 and 2.2.4 suggests that project-internal factors such as prior knowledge, prior experience and project-internal learning activities (PILAs) exert a significant influence on project performance. These three internal project factors allow project groups to build up their absorptive capacity, which can enhance the project groups' ability to evaluate, assimilate, and exploit knowledge from external sources (W. M. Cohen & Levinthal, 1990). The existing literature discusses the factors that are internal to the project group and influence the project performance significantly, as the following subsections show.

2.4.2.1 Prior Knowledge and Prior Experience

Prior knowledge and prior experience can either substitute or complement knowledge inflows (Haas & Hansen, 2005; Argote & Miron-Spektor, 2011; Haas & Hansen, 2005; Nemanich *et al.*, 2010). Knowledge inflows tend to be less important to projects with high prior knowledge (as measured by the cumulative numbers of patents) (Nemanich *et al.*, 2010). Also, knowledge inflows from external sources tend to distract a project group from succeeding in its mission when this project group contains members that have worked extensively on prior projects whose subject matter was relevant to the ongoing project (Haas & Hansen, 2005). This means that a high degree of prior knowledge or a high degree of prior experience can act as a substitute for knowledge inflows (Argote & Miron-Spektor, 2011; Haas & Hansen, 2005).

My review of the literature has caused me to raise two questions. First, does a project group with high prior knowledge generate higher performance when it engages with external sources? If so, is this true for all three critical missions of the national laboratories? To date, few studies that measure the impact of prior knowledge on the relationship between the inflows of knowledge from external sources and project performance have been conducted. It is consequently important to quantify the impact of prior knowledge on project performance because doing so can help us understand how the success of the NLs in mission 3 can contribute to the success in the two other missions. Finally, I contend that *the impact of a project group's prior knowledge on its ability to absorb knowledge from external sources has not been **quantified***. (Research Gap RG-2)

In addition, the existing literature has never addressed the impact of project group members' prior experience with external sources of knowledge on the relationship between the inflows of knowledge from the external sources and project performance. A project group member who has had experience in working or studying with an external source may facilitate (or complement) the inflow of knowledge from the external source. He/she may consequently contribute to improving the performance of the project. Understanding the impact of prior experience with the external sources on project performance can help NLs design their strategy for hiring external experts, recruiting staff and promoting studying or working with the critical sources of knowledge for NLs in TLCs. Finally I contend that the *impact of a project member's prior experience on its ability to absorb knowledge from external sources has not been **quantified***. (Research Gap RG-3)

2.4.2.2 Project-Internal Learning activities (PILAs)

Prior studies (S. Wong, 2004; Bresman, 2010) suggest that PILAs can either impede or encourage knowledge inflows from different pathways. If projects groups have high degree of PILAs, then encouraging project group members to participate more in CLAs can impede the project group's performance especially in project efficiency (S. Wong, 2004). However, CLAs distract from internal project learning in projects with high PILAs, which tends to decrease project efficiency. By contrast, a high degree of PILAs can encourage (or complement) knowledge inflows via VLAs, which enhances project performance (Bresman, 2010). Thus, PILAs are a critical enabler of vicarious learning activities (Bresman, 2010).

To date, no academic study that measures the impact of internal project learning capabilities on the relationship between the inflows of knowledge from external sources and the project performance of NLTs in TLCs has been conducted. R&D project groups, which are highly engaged in project internal learning activities, may be critical to absorbing knowledge from international sources. In contrast, engagement with international sources of knowledge may distract the R&D project groups, which are highly engaged in project internal learning activities to succeed in their missions. The findings pertaining to how a project's internal learning capabilities influence the relationship between knowledge inflows and project performance can help R&D project managers design their strategies for interacting with the four main sources of external knowledge effectively. Finally, I address *the impact of project-internal learning activities in ongoing projects on the relationship between the degree of engagement with external sources of knowledge and the performance of the projects*. To date, *this topic has not been studied in the context of NLTs in TLCs*. (Research Gap RG-4)

2.4.3 Choice of Pathway for Knowledge Inflows into a Project

The choice of pathway for knowledge inflows is another factor that impacts project performance. For example, knowledge inflows that result from searching activities that are related to contextual learning activities (CLAs) have a negative impact on efficiency and innovativeness in NPD projects (Ancona & Caldwell, 1992), yet they have positive impact on innovativeness in service development and manufacturing projects (S. Wong,

2004). Vicarious learning activities (VLAs) tend to have a positive impact on both efficiency and innovativeness in in-sourcing projects (Bresman, 2010).

To the best of my knowledge, no empirical research that characterizes the impact of knowledge inflow from each of the previously mentioned pathways on the performance of NLS in TLCs has been conducted to date. The anticipated empirical findings of this dissertation should be able to extend the understanding about how different pathways of knowledge inflows impact project performance as it pertains to the three critical missions of NLS in TLCs. Selection of pathways for knowledge inflow that align with the critical missions of NLS in TLCs should be able to help project managers gain additional benefits from knowledge inflow.

2.4.4 Sources of External Knowledge for a Project

Sources of external knowledge can also be a key factor that impacts project performance. For example, projects that obtain knowledge from inside their own organization (e.g., the content of electronic documents that have been archived within an organization's database) can improve the time efficiency of the projects (Haas & Hansen, 2007). In contrast, projects that obtain knowledge from sources outside their organization tend to decrease project efficiency because these projects tend to have higher searching and learning costs (S. Wong, 2004).

The importance knowledge from external sources has been discussed in various research streams including absorptive capacity, organizational learning, NIS, Open Innovation and

international technology transfer. The absorptive capacity literature and the organizational learning literature show that a project tends to acquire new knowledge from both inside and outside organization and integrates it with existing internal knowledge (Ancona & Caldwell, 1992; S. Wong, 2004; Haas & Hansen, 2005; Bresman, 2010; Nemanich *et al.*, 2010). According to the literature on national innovation systems (NIS, discussed in section 2.2), institutions within the NIS, such as local universities, government research institutes and LTUs, can serve as sources of external knowledge. In addition, the research stream on international technology transfers (reviewed in section 2.2.1.3) addresses how important knowledge from advanced technological countries, *i.e.* knowledge from outside the NIS of TLCs, is to TLCs, including R&D projects within NIs of TLCs.

Based upon the above literature review, I contend that the impact on the performance of R&D projects of knowledge obtained from inside and outside the NIS has not been studied extensively (if at all). How the engagement with external entities inside and outside the NIS impacts the performance of R&D projects should thus be the subject of further academic study. The results of such academic study may enhance the NIs understanding of knowledge flow to the point where the NIs can adjust their strategies, in order to engage with external institutions much more effectively. Also, policymakers in TLCs should be able to use the findings from this dissertation to make structural adjustments and policy modifications that promote interaction between institutions within the NIS and engagement with institutions outside the NIS.

2.4.5 Summary of Section

Figure 2.4 depicts taxonomy of pathways through which knowledge can enter an R&D project group and mechanisms through which knowledge can be generated internally. It shows that project groups typically gain internal *static* knowledge from prior experience of project members (grafting of people prior to the start of a project) (Huber, 1991) and from prior knowledge (W. M. Cohen & Levinthal, 1990; Nemanich *et al.*, 2010). When starting a new project, internal *dynamic* knowledge can be gained from project internal learning activities (PILAs) (Edmondson, 1999; S. Wong, 2004; Bresman, 2010), which allow group members and technology gatekeepers to share knowledge within their new project groups. Additional knowledge may be obtained from external sources, which include other projects inside organization, other institutes inside NIS, and other institutes outside the NIS. The pathways to obtain knowledge from the external sources can be contextual learning activities (CLAs) (Allen, 1977; Ancona & Caldwell, 1992; Hansen, 1999; Bresman, 2010) or vicarious learning activities (VLAs) (Argote *et al.*, 2000; Edmondson *et al.*, 2003; Darr *et al.*, 1995; Epple *et al.*, 1991; Bresman, 2005; Bresman, 2010). R&D projects tend to integrate knowledge from internal sources and external sources for the creation of new technology, innovative products and innovative services.

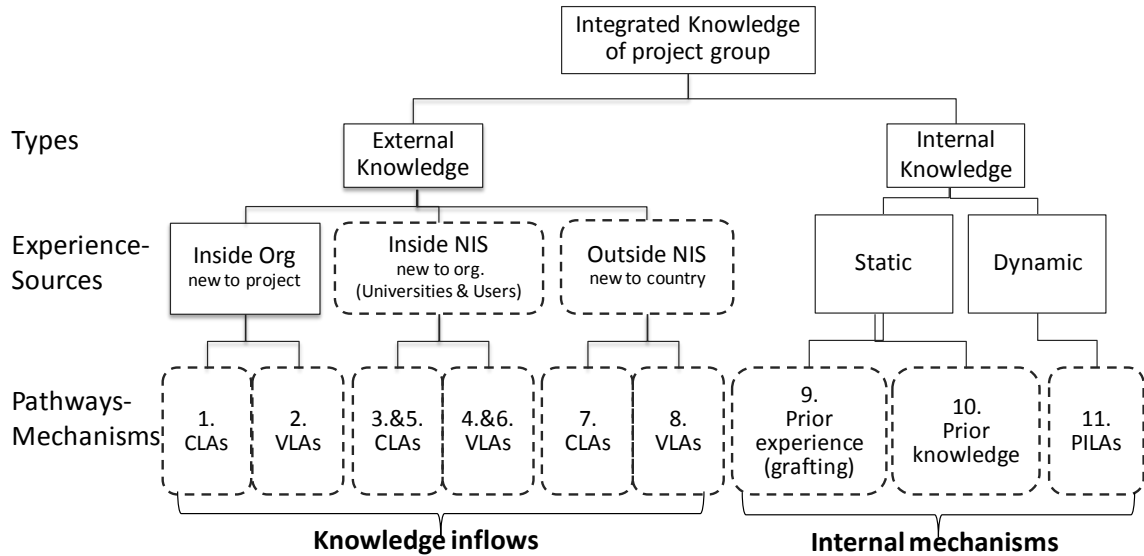


Figure 2.4: Taxonomy of knowledge pathways and knowledge generation mechanisms

Figure 2.4 represents the conclusion of this section. The figure depicts the key factors that tend to influence the impact of knowledge inflows on the performance or R&D projects. The eleven dashed-rectangles in the figure 2.4 refer to subject matter that has yet to be studied extensively.

Table 2.3 clarifies why the eleven dashed-rectangles in figure 2.4 should be a subject for further research. They represent eleven candidate factors pertaining to knowledge inflows that have never been a subject of intensive study; studies about the impact of these candidate factors on the performance of projects within the NLs in TLCs have been lacking in particular. In addition, the impact of the three internal project factors (prior knowledge, prior experience and project internal learning activities) on the relationships

between knowledge inflows from external sources and project performance of NLs in TLCs has never been studied.

Table 2.3: Key factors that have been described in the existing literature and eleven candidate factors that I intend to cover in this dissertation

Author (s)	External Knowledge				Internal Knowledge	
	New to the project from other projects inside org.	New to the project	New to the organization from inside NIS	New to the country from outside NIS	Static experience	Dynamic experience
Ancona and Caldwell, 1992		- CLAs				
Wong, 2004		- CLAs				- PILAs
Haas and Hansen, 2005	- Codified knowledge - Tacit knowledge				- Prior knowledge	
Haas and Hansen, 2007	- Codified knowledge - Tacit knowledge					
Bresman, 2010		- CLAs - VLAs				- PILAs
Nemanich et al., 2010		-Assimilation ability			- Prior knowledge	
Contribution of my dissertation	1. CLAs inside NLs 2. VLAs inside NLs		3. CLAs from local universities 4. VLAs from local universities 5. CLAs with LTUs 6. VLAs with LTUs	7. CLAs from abroad 8. VLAs from abroad	9. Prior knowledge 10. Prior experience	11. PILAs

CLAs = Contextual learning activities;
 VLAs = Vicarious learning activities;
 PILAs= Project internal learning activities

2.5 CONCEPTUAL FRAMEWORK

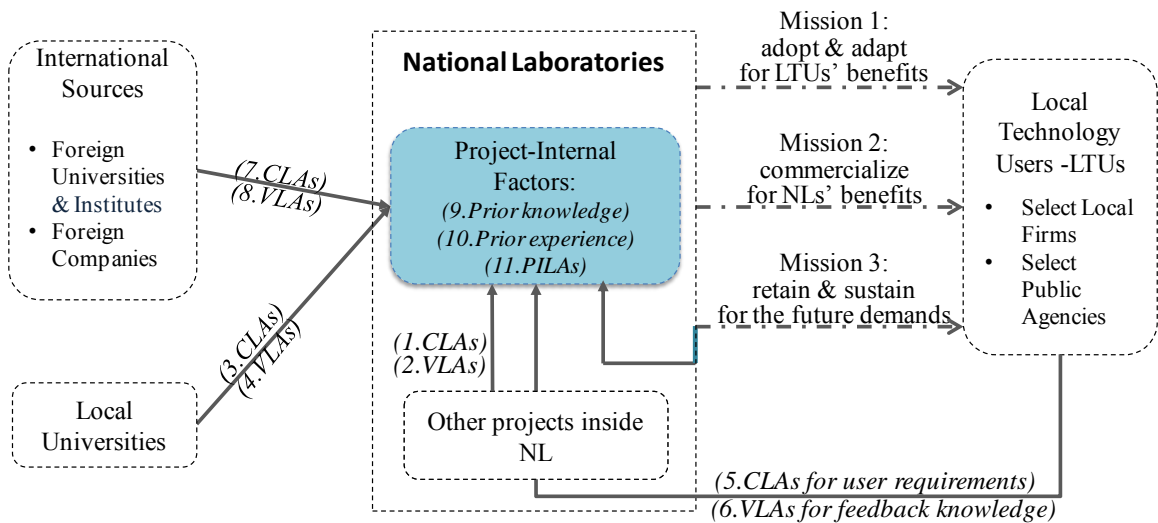


Figure 2.5: Conceptual framework of this dissertation.

Items in (parentheses) are the focus of this dissertation. (The numbers before the CLAs and VLAs refer to figure 2.4 and table 2.3.)

Figure 2.5 illustrates the conceptual framework for this study that has emerged from the literature review in this chapter. This conceptual framework integrates the model for knowledge outflow from figure 2.2 with the model for knowledge inflow from figure 2.3. The result is a model of knowledge flow that transpires within the national innovation systems of technology latecomer countries and is centered on the project groups of the national laboratories.

Figure 2.5 shows that various kinds of knowledge flow into project groups within the NLs of TLCs come from four external sources. Technological knowledge comes from other research and development project groups within NLs and from local universities. User knowledge flows in from the LTUs. Advanced technological knowledge is imported from abroad. The project groups at the NLs in TLCs tend to obtain knowledge from the four external sources via engagement in external learning activities consisting of vicarious learning activities and contextual learning activities.

The knowledge inflows from the external sources can be integrated with the internal knowledge within research and development projects to generate new technological knowledge (W. M. Cohen & Levinthal, 1990). The internal knowledge can come from prior experience of individual project members (through the grafting of people) and prior knowledge of the project groups, which could have been available to the group prior to the beginning of the projects (Huber, 1991). Also an internal source of knowledge can be created by project-internal learning activities (PILAs) while the project is ongoing (e.g., Adler & Clark, 1991; Bohn, 1994; Lapré *et al.*, 2000; Edmondson *et al.*, 2003).

Figure 2.5 is an expansion of figure 1.1, which has been enabled by the literature review in this chapter. Just like figure 1.1, figure 2.5 depicts all the knowledge inflows. However, figure 2.5 also identifies the various mechanisms for knowledge inflows (CLAs and VLAs) and a variety of types of project-internal knowledge. It also shows that the knowledge output generated from the projects tends to flow out of the NLs to the LTUs, and that the impact of this knowledge outflow is mission specific. Performance may thus not only be a function of knowledge inflows, the various forms project-internal

knowledge and the plethora of interactions between the various forms of inflow and project-internal knowledge. It is also likely to be mission specific, and it may depend on the type of inflow mechanism (CLA or VLA). This suggests that *managers have a multitude of potential levers at their disposal to address very specific performance issues.* However, the managers within the national laboratories are currently probably unable to identify these levers because the impact of knowledge inflows and project-internal knowledge on the performance of project groups has not yet been characterized.

2.6 RESEARCH GAPS AND RESEARCH QUESTIONS

In this section, I summarize research gaps pertaining to the impact of managing knowledge inflows on performance of NLs in TLCs, which have been discussed in section 2.1 to section 2.4. I subsequently pose research questions that address these gaps. The literature review shows that the importance of knowledge flow as it pertains to the performance of national laboratories in technology latecomer countries has not yet been established. The following primary research gap has been identified in particular (in section 2.2.6).

Primary Research Gap-- *No quantitative study on the impact of the four main sources of external knowledge and of the three main sources of internal knowledge on the performance of NLs in TLCs has ever been done.*

The primary research gap breaks down into the following series of issues that have not yet been addressed in the academic literature. Every one of these issues comprises a research gap of its own. There are four research gaps in total.

- **Research Gap RG-1** -- *The impact of inflows from external sources of knowledge on the performance of project groups within national laboratories in technology latecomer countries has not been quantified.* (Actually, this topic has not been studied at all.)
- **Research Gap RG-2** --*The impact of a project group's prior knowledge on its ability to absorb knowledge from external sources has not been quantified.*
- **Research Gap RG-3** -- *The impact of a project group's prior experience on its ability to absorb knowledge from external sources has not been quantified.*
- **Research Gap RG-4** -- *The impact of a project group's internal learning capabilities on its ability to absorb knowledge from the external sources has not been quantified.*

There is a one-to-one correspondence between the research gaps from above and the following research questions.

Primary Research Question – *To what degree does engagement with the external sources of knowledge affect the performance of national laboratories in technological latecomer countries?*

- **Research Question RQ-1** – *What is the **relative** impact on the performance of national laboratories in latecomer countries of engaging a) with other project groups within the same organization; b) with the sources of foreign knowledge; c) with sources of user knowledge and d) with other sources of domestic knowledge?*
- **Research Question RQ-2** – *What is the effect of a project group’s **prior knowledge** on the relationship between the project group’s degree of engagement with external sources of knowledge and the project’s performance?*
- **Research Question RQ-3** – *What is the effect of a project group’s **prior experience** on the relationship between the project group’s degree of engagement with external sources of knowledge and the project’s performance?*
- **Research Question RQ-4** – *What is the effect of a project group’s **internal learning capability** on the relationship between the project group’s degree of engagement with external sources of knowledge and the project’s performance?*

Addressing these research questions will hopefully allow me to achieve my research objective, which has been stated as follows at the beginning of section 1.3: to *identify factors pertaining to knowledge inflows that determine the success or failure of research projects in the national laboratories of latecomer countries*. Figure 2.6 illustrates the relationship between my management question, my research objective, the gaps in the existing literature and my research questions.

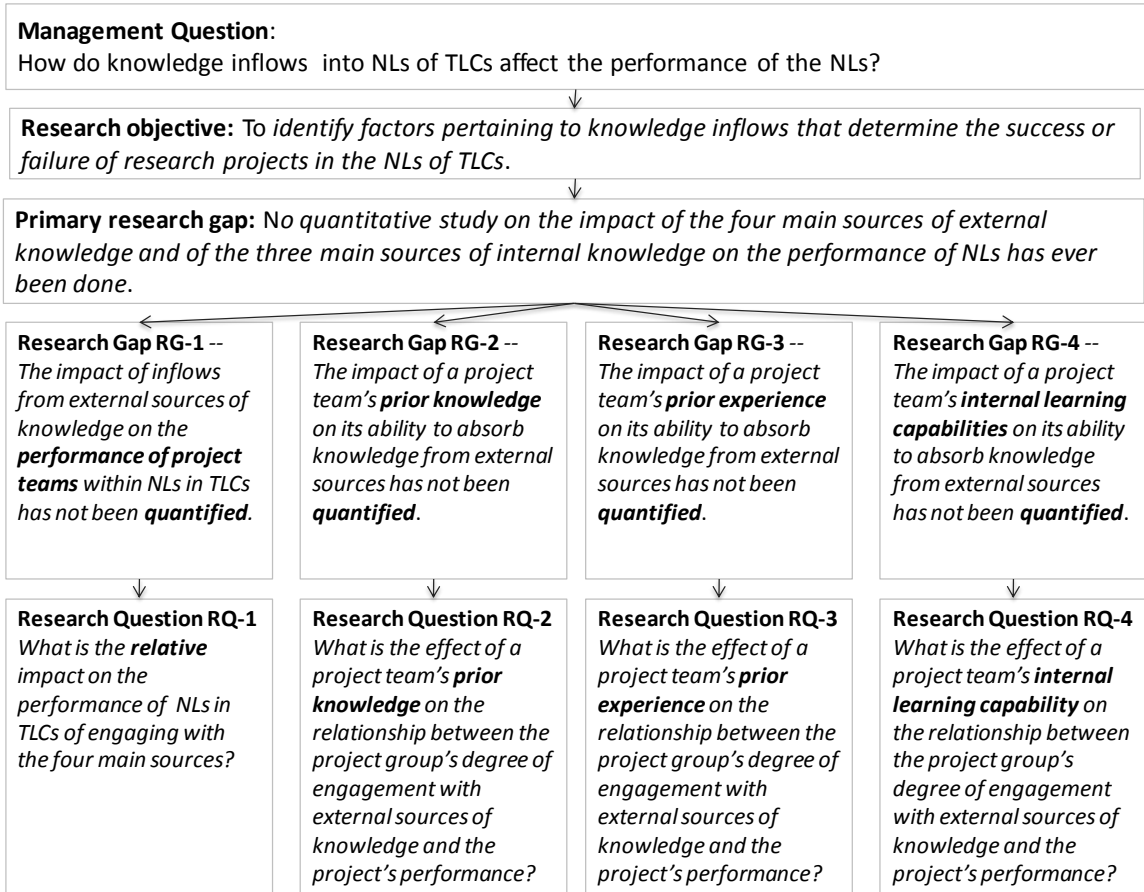


Figure 2.6: The relationship between management question, research objective, research gaps and research questions.

3. RESEARCH HYPOTHESES

This study intends to investigate the impact of the knowledge inflows gained from engagement with the external sources of knowledge on the project performance at the NLS in TLCs. The extent to which each project group engages with external sources of knowledge for the purpose of gaining knowledge inflows from these sources tends to vary from project to project. The different degree of engagement with the external sources of knowledge may affect the performance of each project differently. In addition, the level of internal knowledge of within the projects groups is likely to impact the performance of each project. It may also influence significantly how the degree of engagement with the external sources of knowledge impacts the performance of individual projects. The findings from this study can also help us understand how different degrees of inflow from the four sources of external knowledge into project groups within the NLS in TLCs impact the performance of the projects as they pertain to the three critical missions of the NLS. Finally, the findings of this study may shed light on how project-internal factors impact the performance of individual projects, and how project-internal factors impede or promote knowledge inflows into the NLS in TLCs.

In this chapter, I propose research hypotheses that allow me to investigate how the knowledge inflows into R&D project groups and project-internal factors at the NLS in TLCs impact the performance of research projects, as it pertains to the three critical missions of the NLS. I also propose to assess how the project-internal factors impede or promote the knowledge inflows into NLS in TLCs.

In the following sections, I deconstruct the theoretical framework from figure 2.5 into its conceptual components – the impact on the performance of projects of engagement with other R&D project groups within NLs (section 3.1); engagement with domestic sources of technological knowledge (section 3.2); engagement with LTUs (section 3.3); engagement with international sources (section 3.4); prior knowledge (section 3.5); prior experience (section 3.6); and project internal learning activities (section 3.7). I design a set of testable hypotheses for each conceptual component. The sets of hypotheses that address engagement with external entities (sections 3.1 through 3.4) contain at least one hypothesis that pertains to each critical mission of the national laboratories. Sections 3.5 through 3.7 propose hypotheses, which suggest that internal knowledge either complements or acts as a substitute for knowledge that flows into a project group from external sources. A discussion on how to test all hypotheses that are proposed in this section follows in chapter 4.

Figure 3.1 contrasts the effect of complementarity and substitution in an example that pertains to the NLs in TLCs. In figure 3.1a, prior knowledge complements the degree of engagement with international sources of knowledge; in figure 3.1b, prior knowledge acts as a substitute for the degree of engagement with international institutions. Revenue generation is the performance metric for figure 3.1a and for figure 3.1b.

In figure 3.1a, revenue generation is a rapidly increasing function of the degree of engagement with international sources of knowledge when prior knowledge is high and a slowly increasing function of the degree of engagement with international sources of knowledge when prior knowledge is low. The direct impact on revenue generation is in

the higher domain of engagement with international sources when the prior knowledge is high; the direct impact on revenue generation is in the lower domain of engagement with international sources when the prior knowledge is low.

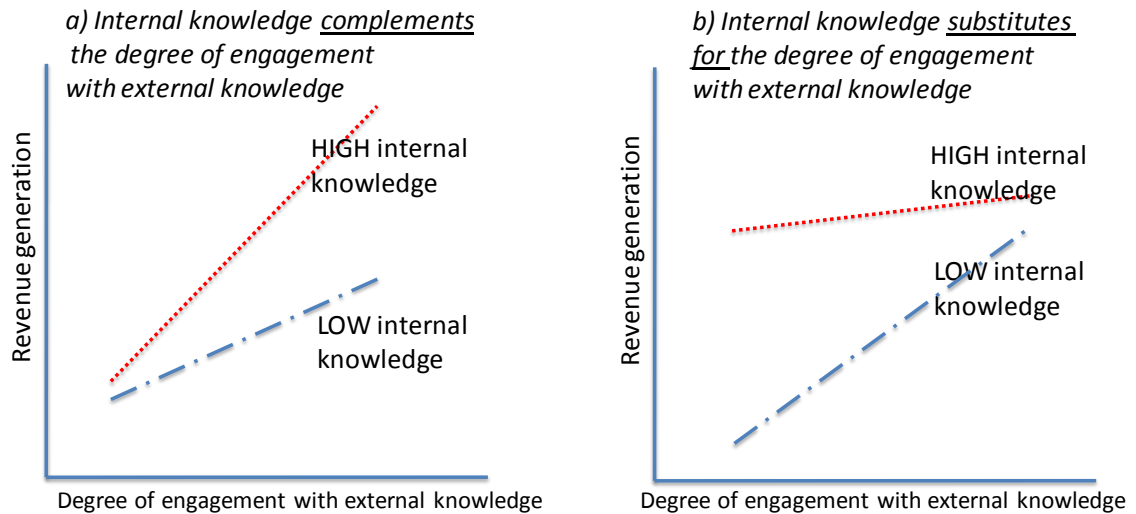


Figure 3.1: Complementarity versus substitution of internal knowledge (prior knowledge)

In figure 3.1b, revenue generation is a rapidly increasing function of the degree of engagement with international sources of knowledge when prior knowledge is low and a slowly increasing function of the degree of engagement with international sources of knowledge when prior knowledge is high. The direct impact on revenue generation is in the higher domain of engagement with international sources when the prior knowledge is high; the direct impact on revenue generation is in the lower domain of engagement with international sources when the prior knowledge is low.

It should be noted that in practice the intersection between the two trajectories in figure 3.1a and figure 3.1b does not necessarily occur near the median of the distribution of the

independent variable. More commonly, the intersection between the two trajectories occurs near the lower end of the distribution in a complementary interaction. By contrast, the intersection between the two trajectories occurs near the upper end of the distribution in a substitutive interaction.

3.1 IMPACT OF ENGAGEMENT WITH OTHER R&D PROJECT GROUPS WITHIN THE NATIONAL LABORATORIES

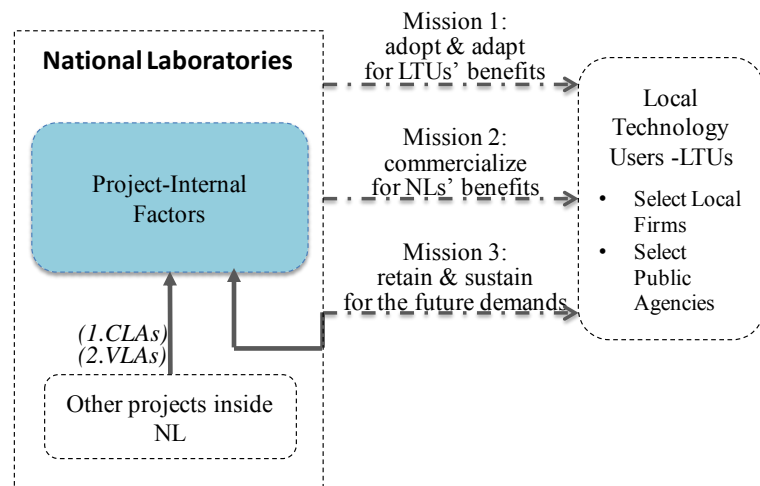


Figure 3.2: Pathways for knowledge flows within NLs in TLCs

Figure 3.2 illustrates how knowledge flows within the national laboratories and how internal knowledge impacts the national innovation system. Members of R&D project groups (especially technology gatekeepers) may engage with other project groups inside NLs, in order to search for technological knowledge that can be integrated with internal knowledge from their ongoing projects. They may learn what other projects are doing by searching the organization's databases (Haas & Hansen, 2005; Haas & Hansen, 2007).

(In my dissertation the NL's constitute 'the organization'.) The members of project groups may also interact with experts from other projects to learn from their experiences (Haas & Hansen, 2005; Haas & Hansen, 2007; Bresman, 2010). Knowledge gains from other projects inside the NLs tend to allow project groups to save time while their projects are ongoing (Haas & Hansen, 2007) and allow them to develop technology that fits with customer requirements (Haas & Hansen, 2007, section 2.3.3). Other project groups within the national laboratories can serve as sources of knowledge, if the project groups within the NLs engage in learning activities that span organizational boundaries (Ancona & Caldwell, 1992; Haas & Hansen, 2005; Haas & Hansen, 2007). Therefore, engaging with other R&D project groups the inside NLs should allow a project group to gain additional knowledge that is useful for its ongoing projects. Engagement with other R&D project groups within the NLs may thus have a significant positive impact on how the project groups contribute to the three critical missions of the NLs.

Hypothesis 1a for Mission 1: Engagement with other R&D project groups within the NLs has a positive impact on the satisfaction of LTUs.

Hypothesis 1b for Mission 2: Engagement with other R&D project groups within the NLs has a positive impact on the NLs' ability to generate revenue for themselves by commercializing technology that they have developed.

Hypothesis 1c for Mission 3: Engagement with other R&D project groups within NLs has a positive impact on the NLs' ability to build R&D capabilities for the future needs of the country.

3.2 IMPACT OF ENGAGEMENT WITH DOMESTIC SOURCES

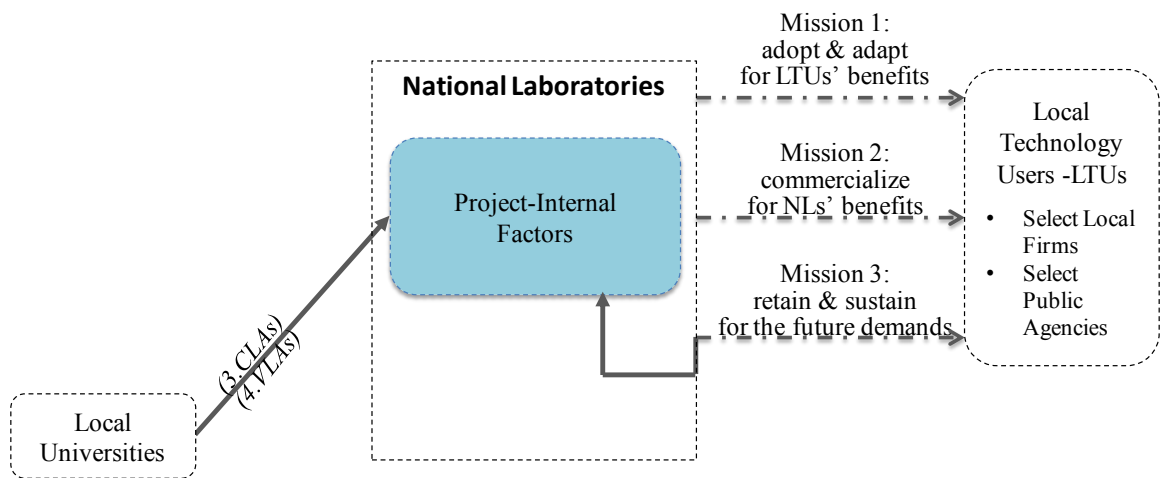


Figure 3.3: Pathways for local knowledge inflows to NLs in TLCs

According to figure 3.3, research projects at national laboratories may obtain knowledge from local universities by engaging in *contextual learning activities* and *vicarious learning activities*. (In my dissertation local universities constitute the only domestic sources of technical knowledge other than the LTUs.) Contextual learning activities include scanning the environment inside the country for technical ideas, collecting technical information or ideas from individuals inside the country, finding out how other R&D project groups within the country but outside the NLs are managing similar projects. Vicarious learning activities include observing the work of researchers within

local universities, inviting domestic experts from local universities to discuss how to avoid repeating past mistakes and talking to them to determine ways of improving the work process.

This study applies the items of contextual and vicarious learning activities from a study by Bresman, 2010), and proposes that knowledge from domestic sources has a positive impact on the performance of national laboratories in latecomer countries.

Hypothesis 2a for Mission 1: Engagement with local universities has a positive impact on the satisfaction of LTUs.

Hypothesis 2b for Mission 2: Engagement with local universities has a positive impact on the NLs' ability to generate revenue for themselves by commercializing technology that they have developed.

Hypothesis 2c for Mission 3: Engagement with local universities has a positive impact on the NLs' ability to build R&D capabilities for the future needs of the country.

3.3 IMPACT OF ENGAGEMENT WITH LOCAL TECHNOLOGY USERS

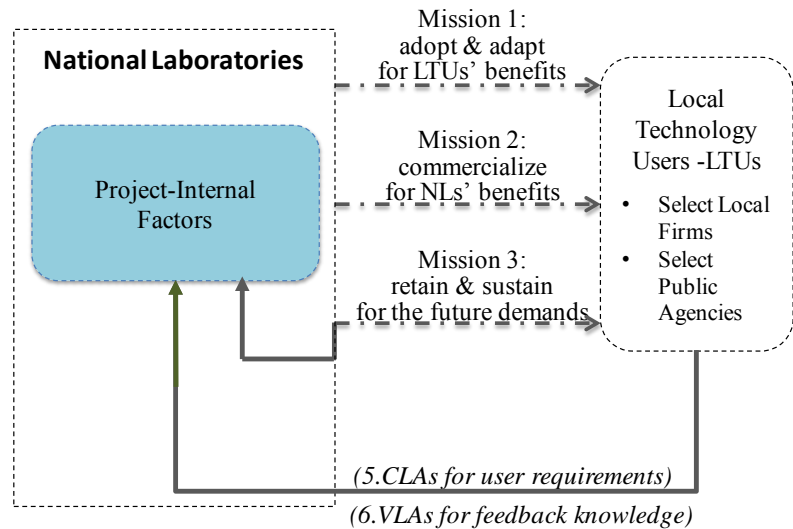


Figure 3.4: The flow of knowledge between NLs and LTUs

Figure 3.4 displays the two main pathways through which NLs are able to gain knowledge from local technology users (LTUs): vicarious learning activities and contextual learning activities. The pathway for knowledge inflow via *contextual learning activities* may occur when individuals in research and development projects scan, search, or explore information about LTUs' requirement (B. H. Johnson, 1992; Lundvall, 2010). The *vicarious learning activities* can be considered as a pathway for feedback knowledge from LTUs. For example, R&D project groups within the NLs may invite or talk to the LTUs about how to improve ongoing projects or how to develop technology that is suitable for LTUs' requirements (Bresman, 2010).

Knowledge inflows from technology users are likely to help a research group understand requirements of technology users and lead to performance improvement (von Hippel,

1988; Lundvall, 2010). Thus, this study proposes that knowledge from local users has a positive impact on the performance of national laboratories in latecomer countries.

*Hypothesis 3a for Mission 1: Engagement with local users has a **positive** impact on the satisfaction of LTUs.*

*Hypothesis 3b for Mission 2: Engagement with local users has a **positive** impact on the NLs' ability to generate revenue for themselves by commercializing technology that they have developed.*

However, most studies of technology users in latecomer countries show that the LTUs in these countries require technologies that help solve near-term, practical problems rather than long-term problems (Intarakumnerd *et al.*, 2002), and they are not ready to adopt advanced technology (Intarakumnerd *et al.*, 2002), because they lack the ability to develop or absorb advanced technology (W. M. Cohen & Levinthal, 1990). Engagement with LTUs in latecomer countries may consequently decrease the performance of the research projects. Thus, I propose the following hypothesis.

*Hypothesis 3c for Mission 3: Engagement with local users has a **negative** impact on the NLs' ability to build R&D capabilities for the future needs of the country.*

3.4 IMPACT OF ENGAGEMENT WITH INTERNATIONAL SOURCES

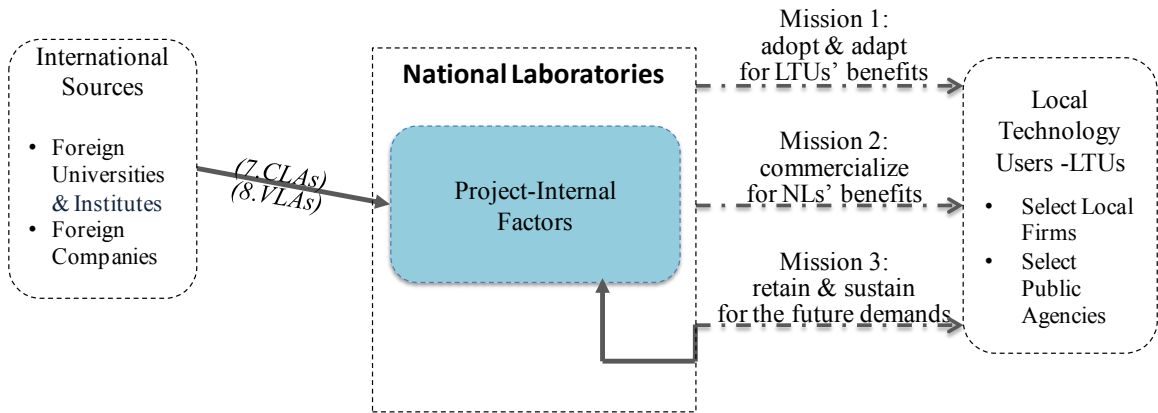


Figure 3.5: Pathways for knowledge inflow from foreign sources

Figure 3.5 shows that that advanced technological knowledge can flow from foreign sources into project groups within the NLs, if the project groups engage in contextual or vicarious learning activities. At the project level *contextual learning activities* are performed by individual researchers, project managers or technology gatekeepers who scan the environment outside the country for technical ideas, collect technical information or ideas from individuals abroad, and try to find out other research groups in the world are doing on similar projects by reading publications or participating in conferences (Bresman, 2010). *Vicarious learning activities* manifest themselves as formal collaboration in research and development or as informal information exchanges between members of the project group and their international network of peers (Allen, 1971; Tushman & Katz, 1980; R. Katz & Allen, 1982). These activities enable members of project groups to observe the work of their partners, to extract lessons to be applied to their projects, to invite experts from abroad to discuss how to avoid repeating past

mistakes and to talk to experts from abroad about ways of improving the work process (Bresman, 2010).

This study proposes that knowledge from international sources that enters project groups within the NLs of TLCs through contextual and vicarious learning has a significant positive impact on the performance of projects that are conducted within the national laboratories in latecomer countries. Thus, I propose the following hypotheses.

*Hypothesis 4a for Mission 1: Engagement with international sources has a **positive** impact on the satisfaction of LTUs.*

*Hypothesis 4b for Mission 2: Engagement with international sources has a **positive** impact on the NLs' ability to generate revenue for themselves by commercializing technology that they have developed.*

*Hypothesis 4c for Mission 3: Engagement with international sources has a **positive** impact on the NLs' ability to build R&D capabilities for the future needs of the country.*

3.5 IMPACT OF PRIOR KNOWLEDGE (COMPLEMENT OR SUBSTITUTE)

The most advanced technological knowledge that flows into the project groups within the NLs of TLCs tends to come from international sources. R&D project groups within the

NLs in TLCs, who want to utilize foreign technological knowledge effectively, may consequently require *prior knowledge* to absorb the more advanced knowledge (W. M. Cohen & Levinthal, 1990). This suggests that prior knowledge *complements* the effect of engagement with international sources on NLs' performance. In contrast, knowledge from international sources that flows into a project group with a high degree of *prior knowledge* acts as a *substitute* for the prior knowledge, which would affect project performance adversely (Haas & Hansen, 2005). Conversely, prior knowledge acts as a *substitute* for engaging with international sources.

Following the logic of figure 3.1, I propose the following hypothesis.

Hypothesis 5a: There is an interaction between engagement with international sources and prior knowledge, which affects project performance.

In principle, the same line of reasoning applies to inflows from other sources of knowledge that are exogenous to the project group. These sources include other R&D project groups within the national laboratories (also known as other R&D units or ORDUs) and domestic sources, such as local technology users and local universities, which are part of the national innovation system but not part of the national laboratories. Knowledge that flows from these sources into a project group with a high degree of *prior knowledge* could act as a substitute for the prior knowledge, which would affect project performance adversely (Haas & Hansen, 2005). Conversely, prior knowledge could act as a substitute for engaging with local universities, local technology users and other R&D project groups within the national laboratories. On the other hand, internal knowledge

could be complementary and enhance a project group's capacity to absorb knowledge from these sources (W. M. Cohen & Levinthal, 1990); then the impact on performance would be positive.

Pursuing the logic of figure 3.1, I propose the following hypotheses.

Hypothesis 5b: There is an interaction between engagement with local universities and prior knowledge, which affects project performance.

Hypothesis 5c: There is an interaction between engagement with local technology users and prior knowledge, which affects project performance.

Hypothesis 5d: There is an interaction between engagement with other R&D project groups within the national laboratories and prior knowledge, which affects project performance.

3.6 IMPACT OF PRIOR EXPERIENCE (COMPLEMENTARY)

Project members who have experience in working on other R&D projects inside the NLs can be considered an important pathway for the ongoing projects to gain access to new technological knowledge, because other projects inside the NLs may have accumulated experience in researching and developing technology that can complement the ongoing project (Haas & Hansen, 2005; Haas & Hansen, 2007; Bresman, 2010, section 2.4.2.2).

This suggests that prior experience with other R&D project groups inside NLs *complements* the effect of engagement with other R&D project groups inside NLs on NLs' performance. Following the logic of figure 3.1, I propose the following hypothesis.

Hypothesis 6a: There is an interaction between engagement with other R&D project groups inside the NLs and prior experience, which affects project performance.

In addition, researchers within the NLs' who graduated from local universities or had working experience with them may move to work for the NLs. The NLs can gain academic knowledge in specific areas, which local professors have been researching or developing. This can be a pathway for access to local sources of knowledge via grafting (Huber, 1991). This suggests that prior experience with local universities *complements* the effect of engagement with local universities on the NLs' performance. Following the logic of figure 8, I propose the following hypothesis.

Hypothesis 6b: There is an interaction between engagement with local universities and prior experience, which affects project performance.

Another strategic pathway to gain knowledge from LTUs via grafting may occur in some critical research and development projects. The NLs may consequently hire project managers or technology gatekeepers who have working experience in selected firms or in targeted public agencies. NLs may also recruit new members from or exchange people with LTUs. This suggests that prior experience with LTUs *complements* the effect of

engagement with LTUs on NLs' performance. Following the logic of figure 8, I propose the following hypothesis.

Hypothesis 6c: There is an interaction between engagement with LTUs and prior experience, which affects project performance.

In addition, prior to the start of an R&D project, the NLs also tend to gain advanced technological knowledge from outside the NIS by grafting people who have experience in working or studying abroad (Hoekman *et al.*, 2005). These people may have informal relations with technology experts in specific areas (Gil *et al.*, 2003) and can facilitate technology transfer from international to local institutions. Thus, prior experience with international sources of knowledge can facilitate knowledge inflows into NLs and can increase the impact of knowledge inflows on project performance. This suggests that prior experience with international sources *complements* the effect of engagement with international sources on NLs' performance. Following the logic of figure 3.1, I propose the following hypothesis.

Hypothesis 6d: There is an interaction between engagement with international sources and prior experience, which affects project performance.

3.7 IMPACT OF PROJECT-INTERNAL LEARNING ACTIVITIES (PILAs) (COMPLEMENT OR SUBSTITUTE)

Two questions concerning knowledge inflows still need to be asked. First, *do PILAs impede or encourage knowledge inflows from different sources of knowledge?* If so, then *to what degree do a project group's internal learning capabilities impact the group's ability to absorb knowledge from the external sources?* Based on the literature review in chapter 2, project-internal learning activities (PILAs) help group members learn from experience within their own groups (Edmondson, 1999; S. Wong, 2004; Bresman, 2010). Projects that strongly engage in PILAs should thus be able to absorb more advanced technological knowledge from abroad. This suggests that project-internal learning activities **complement** the effect of engagement with international sources on NLs' performance. In contrast, Haas & Hansen, 2005, have found that project internal learning activities act as a substitute for the effect of engagement with external sources on organizational performance. This suggests that project internal learning activities **substitute** for the effect of engagement with international sources on NLs' performance. Thus, I propose that the following hypotheses will be confirmed.

Hypothesis 7a: There is an interaction between engagement with international sources and project-internal learning activities, which affects project performance.

NLs in TLCs typically intend to promote collaborations between NLs and local universities, so that they can facilitate knowledge exchange between these two parties.

Projects with higher degree of PILAs may thus be more motivated to engage in a joint learning process with local universities. This suggests that project internal learning activities **complement** the effect of engagement with local universities on NLs' performance. In contrast, interaction with domestic sources of knowledge may distract project groups with high PILAs from their internal project learning process and lead to a decrease in project performance (Haas & Hansen, 2005). This suggests that project internal learning activities **substitute** for the effect of engagement with local universities on NLs' performance. Thus, I propose that the following hypotheses will be confirmed.

Hypothesis 7b: There is an interaction between engagement with local universities and project internal learning activities, which affects project performance.

The NLs in TLCs typically intend to develop technology that fits with local demands; thus interaction with LTUs is critical to their success. Group projects with high level of PILAs should be able to find suitable solutions for the LTUs, which are based on their internal learning processes. This suggests that project-internal learning activities **complement** the effect of engagement with local users on NLs' performance. Following the logic of figure 3.1, I propose the following hypothesis.

Hypothesis 7c: There is an interaction between engagement with local users and project internal learning activities, which affects project performance.

A similar line of reasoning applies to prior experience and knowledge inflows from other R&D project groups within the national laboratories. Therefore, I propose the following hypothesis.

Hypothesis 7d: There is an interaction between engagement with other R&D project groups within the national laboratories and project internal learning activities, which affects project performance.

4. RESEARCH METHODOLOGY

The research that has been conducted for this dissertation is survey based. I designed a questionnaire that consisted of questions pertaining to knowledge inflow, project-internal knowledge and various measures of organizational performance. I administered this questionnaire in person to 123 project managers within NSTDA, the national laboratories of Thailand. The survey data was entered into a spreadsheet and analyzed using the SPSS statistical analysis software. The results of the data analysis are presented in Chapter 5.

In this chapter, I discuss the research methodology that was used to conduct this study. First, I identify the unit of analysis and the research setting of the study. I subsequently propose a research framework and describe the variables that I intend to measure. Next, I address how to measure these variables and how to collect data for each variable. I also discuss the validity and reliability of the measures. At the end of this chapter, I describe my approach to data analysis.

4.1 UNIT OF ANALYSIS

The success of a national laboratory is contingent upon the number of projects that it completes and the perceived impact these projects have on the bottom-line of LTUs and the wellbeing of the country at large (L. Kim, 1980; L. Kim, 1997; P. L. Chang & Hsu, 1998; K. Lee & Lim, 2001, section 1.3). I consequently make the research project my unit of analysis.

4.2 RESEARCH SETTING

In the study to be performed in this dissertation, I use data from Fagerberg, Srholec, and Knell (2007) and additional articles to assess the level of a country's economic development. I classify countries according to technological sophistication by comparing the number of patents, science articles and engineering articles they generate per citizen per year, as well as by their ranking on the ICT infrastructure index. I differentiate between 1) countries such as United States, Switzerland, Germany, Japan, Sweden, which are technologically advanced (Lall, 1992); 2) countries such as Korea, Taiwan, Singapore, which are "catching up" (Intarakumnerd *et al.*, 2002) both technologically and economically; 3) technological latecomer countries such as Thailand, Indonesia, Chile and Pakistan, which lag behind the other groups of countries but are making efforts to advance (Fagerberg *et al.*, 2007); 4) and technological laggards (e.g., most countries in sub-Saharan Africa), which until recently have made few efforts to advance technologically and, in general, are not viewed as technologically competitive (Fagerberg *et al.*, 2007). In my dissertation research, I shall focus on technological latecomer countries, whose national laboratories and national innovation systems are likely to benefit more from my dissertation than countries in the other groups.

According to Intarakumnerd *et al.*, 2002, technological latecomers are characterized as follows: 1) they possess very limited capabilities to facilitate and produce intensive technological learning; 2) the linkages between users and producers in technological latecomer countries are generally weak; 3) the co-operation of firms in the same and related industries is not strong, 4) technology spillover from multinational corporations to

local industries tends to be low, and 5) the linkages between public research (at universities and national laboratories) and industries are weak. All five of these attributes of technological latecomer countries are within the scope of my research.

The National Science and Technology Development Agency (NSTDA) in Thailand has been chosen as a setting for the proposed study because is a typical example of a national laboratory in a latecomer country. The NSTDA is considered a significant source of scientific and technological knowledge for the country of Thailand. The NSTDA consists of four national research institutes: biotechnology, materials, electronics and computers, nanotechnology. These research centers operate 95 laboratories. The NSTDA's laboratories initiate about 400 new research projects per year to serve technological requirements of the country. Each laboratory runs multiple projects. Thus, a large sample of projects spanning a variety of industries and technologies is available for study.

Typically, the NSTDA's research projects can be categorized into a group of ten platform technologies, four cross-cutting programs and five areas that have been targeted for commercialization. Platform technologies tend to focus on basic research pertaining to technologies that feed the cross-cutting programs and the five target areas. Therefore, activities that transpire within the platform technology project groups are considered an early stage of an R&D process that advances towards accomplishing the third critical mission of the national laboratories. The research projects that are conducted under these platforms also aim to advance the scientific and technical know-how of the country, thereby contributing significantly to the third critical mission of national laboratories. The ten platform technologies comprise genome technology; microbial biotechnology; agro-

biotechnology; devices and systems technology; service informatics; computer aided design, engineering, and manufacturing; material design and production simulation; nano-coating; nano-encapsulation; and functional nanostructure (NSTDA, 2011).

Cross-cutting programs primarily consist of applied research projects that develop technologies based on the know-how of the NSTDA's or its external research partners. The NSTDA develops these technologies to a level of maturity at which they are ready for demonstration in the five target applications. The four cross-cutting programs sponsored by the NSTDA are functional materials; sensor and intelligent systems; digital engineering; and service research (NSTDA, 2011).

The last group of NSTDA projects aims to promote the five target areas that are considered to have a high impact on social and economic development of Thailand. The five target areas include agriculture and food; energy and environment; health and medicine; bio-resources, communities and the underprivileged; and manufacturing and service industries (e.g., hard disc drives, air conditioners and automobile parts). This group of projects is required to turn the internal know-how generated by the platform technologies and cross-cutting programs into products and services. This group also is requested to define external stakeholders, which should be able to support research groups in defining marketable research topics, bringing technologies to the market, and finance the research projects within the target areas (NSTDA, 2011). In Thailand these stakeholders are the LTUs.

4.3 RESEARCH FRAMEWORK

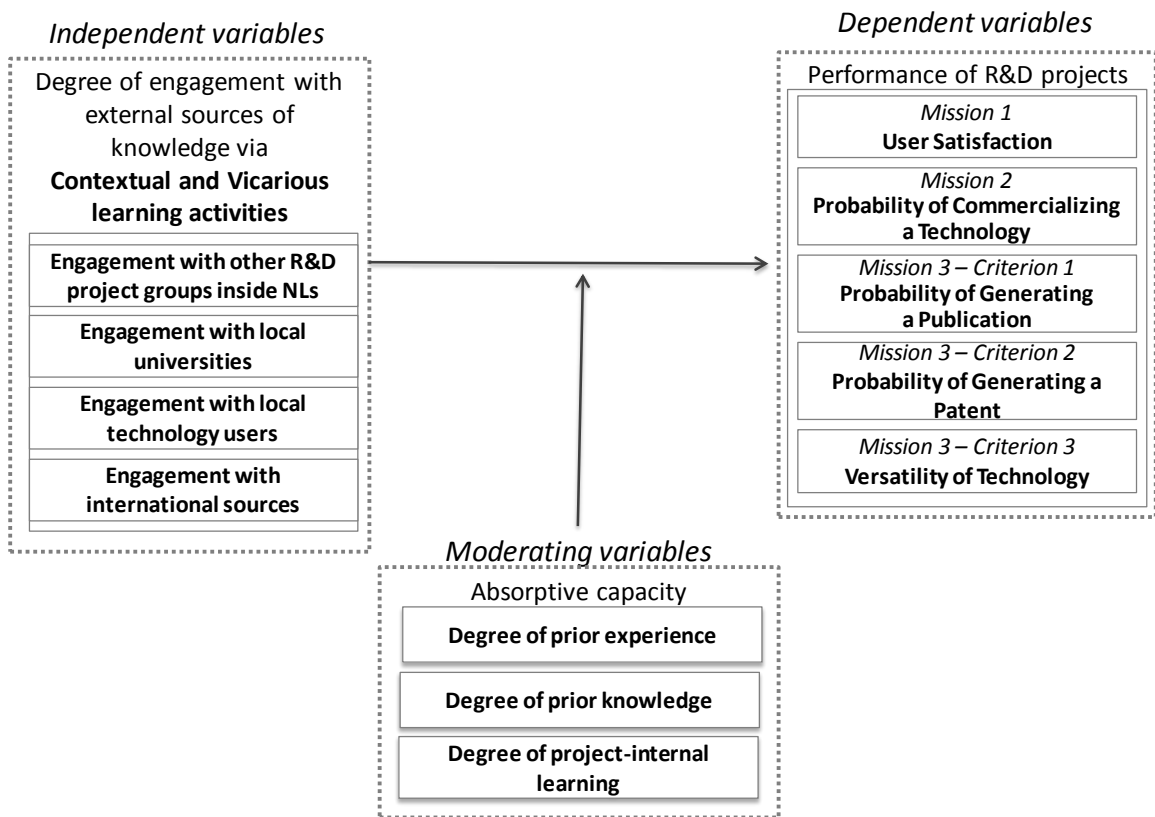


Figure 4.1: Research framework of this study

Figure 4.1 depicts the research framework of this study. This framework contains three sets of variables: independent variables to measure the degree of engagement with external sources of knowledge of each project group; moderating variables to measure the level of internal knowledge of each project group and dependent variables to measure the project performance. The details of measuring the variables are discussed in the section 4.5. In the following section, I discuss a research process that intends to guarantee validity and reliability of the measures.

4.4 VALIDITY AND RELIABILITY OF MEASURES

The validity of measures is generally determined by examining whether or not two or more ways of measuring the same construct give the same results (Judd *et al.*, 1991, p. 26). To develop a good measure, D. R. Cooper & Emory, 1995, proposed that a researcher has to be concerned about content validity, construct validity, criterion validity, and reliability of the measure. Also, the research needs to consider whether administering the planned survey is practical.

Table 4.1: Validity, reliability, and practicality of the survey questions

Items (Cooper and Emory, 1995)	Purpose	How to test
I. Content validity	Measure the extent to which the questions provide adequate cover of the topic under study	Before conducting the survey: <ul style="list-style-type: none"> - use experts' evaluation on the survey questions - provide the purpose of the questions - ask experts to comment the questions
II. Construct validity	Answer "how we measure what we want to measure" (Judd <i>et al.</i> , 1991, p. 29)	Before conducting the survey: <ul style="list-style-type: none"> - use item scales from literature review - develop new item scales based on theoretical review
		After conducting the survey: <ul style="list-style-type: none"> - use factor analysis (Cooper and Emory, 1995)
III. Criterion validity	Measure the degree to which the predictor is adequate in capturing the relevant aspects of the criterion	After conducting the survey: <ul style="list-style-type: none"> - use correlation (Cooper and Emory, 1995)
IV. Reliability	Measure the degree to which questions are homogeneous and reflect the same underlying constructs	After conducting the survey: <ul style="list-style-type: none"> - use internal consistency approach (Cooper and Emory, 1995; Field, 2005) - by measure Cronbach's Alpha Coefficient, - which coefficient value should be higher than 0.7 for reliable scales (Hair <i>et al.</i>, 1995; Field, 2005)
V. Practicality	Consider operational needs in terms of economy, convenience, and interpretability	Before conducting the survey: <ul style="list-style-type: none"> - Expense for conducting the survey - Easy to administer - Response rate

Table 4.1 presents the purpose of testing the validity, reliability, and practicality of the survey questions and how to test these criteria. The following section will discuss these issues in detail.

4.4.1 Content Validity

Content validity measures the extent to which the questions provide adequate cover of the topic under study. A test of the validity of the content can be conducted prior to administering the survey. A researcher can use expert opinion to evaluate the survey questions (D. R. Cooper & Emory, 1995). In this study, I will discuss the purpose of each survey question with experts who work in areas that are relevant to my research, and I ask them to comment on the questions.

4.4.2 Construct Validity

Construct validity pertains to “how we measure what we want to measure.” It addresses the question “To what extent are the constructs of theoretical interest successfully operationalized in the research?” (Judd *et al.*, 1991, p. 29) Trochim & Donnelly, 2001, linked construct validity to the data gathering and the measurement stage in research. As mentioned earlier, the research performed in this study conducts hypothesis testing. In this type of research, the researcher has to design independent variables and dependent variables and know how to measure them (Judd *et al.*, 1991).

To construct the proper items for independent and dependent variables, “researchers can choose among different alternatives, such as applying existing measurement scales,

conducting exploratory preliminary studies, making theoretical considerations, or drawing on experiences from practice” (Homburg and Giering, 1996, p. 12, as cited by Herzog, 2008). The first approach of applying existing scale items comes with the major advantage that it allows for comparing results across different studies. Diller (2004) also proposed that “generating new scale items should be avoided whenever possible, because otherwise this will result in a plethora of different measurement scales in the underlying research fields” (Diller, 2004, p. 177 cited by Herzog, 2008). We can observe the second approach of conducting preliminary exploratory studies in the work of Ancona & Caldwell, 1992 and Bresman, 2010. Their studies intend to identify activities pertaining to external engagement of individual group members. In addition, some research may use mixed approaches to construct items in questionnaire such as theoretical consideration and experience of experts (e.g. Daim, 1998); others generate a set of questions that is based on previously existing measurement scales and theoretical considerations (e.g. Lichtenthaler, 2006b; Herzog, 2008). In this study, I will apply the items scale from the exploratory studies of Ancona & Caldwell, 1992, and Bresman, 2010, to measure external learning activities of R&D projects. In cases where no validated scales exist, I develop new scales based on the theoretical descriptions provided in the literature as discussed in section 4.3 and validate them in a pilot test. In addition, after conducting the survey, this study uses factor analysis to address construct validity (D. R. Cooper & Emory, 1995). Factor analysis helps determine whether the expected relationships among variables exist (Murphy & Davidshofer, 1991, p. 103). See details in appendix C.

4.4.3 Criterion-Related Validity

A criterion is a measure that can be used to determine the accuracy of a decision. It is also known as a dependent variable or an output variable. In psychometrics, the validity of a criterion is a measure of how well a variable or a set of variables predicts the outcomes based on data from other variables (Murphy & Davidshofer, 1991; Pennington, 2003). Criterion validity measures the degree to which the predictor is adequate in capturing the relevant aspects of the criterion (D. R. Cooper & Emory, 1995). The correlation between the predictor and a measure of the outcome (or the criterion) provides an overall measure of the accuracy of predictions. The correlation between the predictor scores and criterion scores can be considered as a measure of the validity of decision (Murphy & Davidshofer, 1991). To confirm the criterion-related validity, a researcher can use correlation (D. R. Cooper & Emory, 1995). In this study, the measures of project performance that contributes to the three missions of NLs serve as criteria for evaluating the success of R&D projects. The degree of engagement with the four main external sources of knowledge and the extent to which a project group can absorb inflows of these four external sources of knowledge constitute the predictors in this study. Thus, after conducting the survey, this study assesses the criterion-related validity from correlation coefficients between the predictors and the criteria. These coefficients can range, in absolute value, from 0.0 to 1.0 (Murphy & Davidshofer, 1991); appendix C addresses how to interpret these coefficients.

4.4.4 Reliability

This study will use Cronbach's alpha to assess the reliability of the items as presented in questionnaire B. Hair *et al.*, 1995, and Field, 2005, suggested the value of Cronbach's alpha should be higher than .70 for a reliable scale. However, the threshold value may decrease to .60 in exploratory research (Hair *et al.*, 1995).

4.4.5 Practicality

D. R. Cooper & Emory, 1995, suggest that a researcher should consider operational needs in terms of economy, convenience, and interpretability before conducting the survey. The expense for conducting the survey, the ease of administering the survey, and the response rate should be criteria of practicality for a research study.

The practicality of conducting a survey is one of the two main reasons that I design to use R&D project groups within the 95 laboratories of the NSTDA as the unit of analysis. (The other reason is that Thailand is a technology latecomer country.) I obtained authorization to conduct this research from I requested NSTDA's top management, which enabled me to administer my survey in person. As a result, I had no need to send out direct mail, and I achieved a near-100% response rate. Delivering the survey in person also allowed me to make sure that the respondents interpreted the questions in the survey in a similar way. I validated the interpretability of the survey questions by a pilot study (for details, please see the following section).

4.5 MEASURES

In this dissertation, most of the independent variables and moderating variables are measured using Likert scales; a few are measured by ordinal scales. Dependent variables are measured by using Likert scales and objective data. To ensure construct and content validity of the measures, I used a two-step design. First, I used item scales from the existing literature and developed new item scales based on theoretical review. This endeavor resulted in a first draft of a questionnaire, which has been presented in appendix B of my original research proposal (Ploykitikoon, 2012). I subsequently evaluated the measures by recruiting 25 experts who work in areas that are relevant to the subject of my dissertation. The experts were asked to evaluate measures in the survey questions with respect to ease of response. As a pilot test of the survey, I also asked the experts to answer the questions in the first draft of the questionnaire. The feedback from the experts was integrated into the final design of the questionnaire, which is presented in appendix B of this document. Details regarding the variables that were used as measures are given in the subsections of this section.

The experts that validated the measures came from three groups of people. The first group consisted of 10 project managers who are professors and students at Portland State University's Department of Engineering and Technology Management (ETM) who managed projects in private industry. These projects developed technology in the same technical areas that are under study in this dissertation. The second group was composed of 10 project managers who are project managers at national laboratories that are under study in my dissertation. They were excellent candidates for evaluating the ease of

response of the survey, because the same survey would be administered to their peers. The last group 5 consisted experts who are program directors at national laboratories. They were excellent candidates for evaluating the ease of response of the output variables that measured the performance of project groups, in part because it is part of their job to evaluate the performance of projects within NSTDA.

4.5.1 Measuring Independent Variables

My approach to measuring independent variables follows that of Ancona & Caldwell, 1992, and Bresman, 2010, who measure the impact of external sources of knowledge on organizational performance. These authors develop items scales that can be used to quantify the degree of engagement with external sources of knowledge, just like I did. However, in contrast to my proposed research, Ancona & Caldwell, 1992, and Bresman, 2010, do not differentiate among a variety of external sources of knowledge. Furthermore, Ancona & Caldwell, 1992, and Bresman, 2010 observed organizations in the private sector, whereas my dissertation research investigates an organizational environment comprised of public and private institutions. I believe that these differences in context are sufficiently minor for me to be able to apply the approaches used by Ancona & Caldwell, 1992, and Bresman, 2010, to my research setting.

According to Ancona & Caldwell, 1992, and Bresman, 2010, contextual learning consists of two main activities that enable knowledge inflows: 1) scanning the environment for information and 2) collecting information from the environment. Thus, I measure contextual learning with a two-item scale: one item elicits information from the

respondent that quantifies a project group's propensity for scanning its environment for information; the other quantifies a project project's propensity to collect information about its environment. These measures act as proxies for the degree of knowledge inflow into the project group. I apply these items to all potential sources of knowledge under investigation: international sources such as foreign universities and foreign owned companies; domestic sources such as local universities and LTUs, and other project groups within the national laboratories. (Please see questions 11 through 18 in appendix B.) LTUs are referred to as targeted customers in the survey questions because NSTDA specifically targets local technology users as customers.

According to Bresman, 2010, vicarious learning includes two principal activities that facilitate knowledge inflows: 1) inviting experts to discuss how to avoid repeating past mistakes and 2) talking to experts to extract lessons learned to be applied to the project and to determine ways of improving the work process. I measure vicarious learning with a two-item scale: the first item quantifies a tendency to invite external experts for discussing lessons learned from the project's past experiences; the second item extracts the project group's propensity to talk to external experts, in order to discuss lessons learned from the experts' past experiences. In my questionnaire, I use these items as proxy measures for the degree of engagement with external sources of knowledge. Once again, I applied these items to all potential sources of knowledge under investigation: international sources such as foreign universities and foreign owned companies; domestic sources such as local universities and LTUs (which are referred as targeted customers in

the survey questions), and other project groups within the national laboratories. The items pertaining to vicarious learning are elicited in questions 19 through 28 in appendix B.

Based upon input from the 20 experts in group 1 and 2, I decided to differentiate between two types of LTUs—those that own production units and those that act as end users. LTUs with production units tend to be private companies who have capabilities to scale-up technological knowledge from the national laboratories. End users tend to be persons, private companies or government agencies that are likely to be the customers of LTUs with production units; they have no capabilities to scale-up technological knowledge from the national laboratories. End users and LTUs with production units are not mutually exclusive categories. It is possible for an end user to have a production unit, but it is not possible for an LTU to not be an end user and not have a production unit.

4.5.2 Measuring Moderating Variables

It has been proposed in section 2.4.3, that the impact of external sources of knowledge on project performance is affected by the project group's capacity to absorb external knowledge. This absorptive capacity depends upon 1) the degree of relevant experience that the project group has obtained from grafting appropriate technical personnel, 2) the degree of relevant knowledge that the project group has accumulated from previous projects, and 3) the degree of internal learning activities that transpire while the project is active. Variables that measure prior experience, prior knowledge and internal learning activities are described in the following subsections. They are classified as moderating

variables because they tend to impact the relationship between independent variables and dependent variables (see figure 13).

4.5.2.1 Prior Experience

The degree of relevant prior experience that a project group possesses at the outset of the project is measured by whether at least one group member has relevant prior experience and by the extent of that experience. A project group member's relevant prior experience can consist of post-graduate study or practical work experience in a field that is related to the subject matter covered by the project under study (Zucker *et al.*, 1998; Almeida & Kogut, 1999; Antal & Walker, 2011; Hoekman *et al.*, 2005; Ploykitikoon & Daim, 2010; Chen & Sun, 2000; Gil *et al.*, 2003). Also, based on the principle of absorptive capacity, W. M. Cohen & Levinthal, 1990, argue that not all members of a project group need to interact with external entities. Instead, the project group may interact with its environment via a technology gatekeeper (Allen, 1971; Tushman & Katz, 1980), who takes a lead role in the evaluation and assimilation of external knowledge.

Five kinds of prior experience have been identified for the purpose of this study (in section: 1) post-graduate study at foreign institutions of higher learning; 2) post-graduate study at local universities; 3) work experience at a foreign-owned company;¹³ 4) work experience at local targeted customers; and 5) having worked on projects outside the project group but inside the national laboratories. I consequently propose to measure

¹³ Work experience at a foreign-owned company could be overseas or within Thailand.

prior experience with a five-item scale: the first item quantifies the extent of educational experience from abroad; the second item elicits the extent of educational experience at local universities; the third item draws out the extent of work experience at a foreign-owned company; the fourth item quantifies the extent of work experience with targeted customers (LTUs); and the fifth item extracts the extent of work experience within other project groups inside the national laboratories. These items act as proxy measures for the extent of prior experience at external sources of knowledge that resides within an R&D project group at the outset of a project. The items are presented in questions 33 through 37 in Appendix B.

4.5.2.2 Prior Knowledge

Nonaka, 1994, argues that organizations create knowledge in a four-stage process that resembles a spiral. First, tacit knowledge is generated through socialization; this knowledge is subsequently converted to explicit knowledge in an externalization process, combined with other explicit knowledge and finally internalized (converted to tacit knowledge) by other parts of the organization. This process repeats, causing new knowledge to be created in and spread across the organization (Nonaka, 1994).

The total prior explicit knowledge within an R&D project group pertaining to subject matter related to the project under study can be estimated by the total number of patents, copyrights and publications pertaining to the study that the group has accumulated prior to the start of the project under study (Matusik & Heeley, 2005; Smith *et al.*, 2005 cited by Nemanich *et al.*, 2010). After validating the questionnaire in the pilot test with 20

experts from group 1 and 2, I decided ask the respondents to rate the total number of patents and publications that were related to the project and had been generated prior to the outset of the project on a 6-point Likert scale (see appendix B, question 38). I also elicited the number of patents and publications directly (see appendix B, questions 7 through 10).

The notion that prior knowledge about the core technology to be developed could affect project performance came up during the pilot test. The experts from group 2 indicated that this kind of knowledge could be important. I subsequently added a question that elicits the level of knowledge about the core technology on an ordinal scale to the questionnaire (see question 7 in appendix B). This question does not ascertain whether knowledge about the core technology is tacit or explicit.

4.5.2.3 Project-internal learning activities (PILAs)

According to Edmondson, 1999, and Bresman, 2010, internal project learning includes the four main project-internal learning activities (PILAs) that allow project groups to absorb knowledge inflows: 1) taking time to figure out ways to improve the work process; 2) reflecting on the group's work progress; 3) speaking up to test assumptions concerning issues that are under discussion among the project group members; and 4) identifying new information that leads to changes. I therefore propose to measure PILAs with a four-item scale. (Please see questions 29 through 32 in appendix B.)

4.5.3 Measuring Dependent Variables

The dependent variables or output variables consist of performance measures that indicate how research and development projects contribute to the three basic missions of NLTs in TLCs. The performance measures for each of these missions are discussed below.

4.5.3.1 Measuring the Performance of Mission 1

According to Spann *et al.*, 1995, user satisfaction can be used to assess how effectively a research and development organization within a national laboratory transfers knowledge and technology out of the laboratory. In this study, LTUs are mentioned as the main technological users of NLTs' technology. Therefore, the degree of satisfaction of the LTUs should be an excellent proxy measure for how well the NLTs in TLCs are performing their first mission (adopting and adapting technology to suit with local demands). During the pilot test, I discovered that best approach for eliciting this information turned out to be asking project managers the following question (Q.39 in appendix B of this dissertation): Based on the results of this project, do you think that the targeted customers of this project will have another collaborative project with your project group in the near future?¹⁴ The output variable associated with this measure is henceforth referred to as OV1.

¹⁴ Originally, I had proposed a two-item scale. I let the respondent rate how the users of the technological innovation that was developed in the project under study were satisfied with that technological innovation as compared to technological innovations generated in other projects. (Please see question 51 and 52 in appendix B of Ploykitikoon, 2012.) I subsequently validated the questionnaire during the pilot test with 5 program directors, who suggested that project managers should be able to provide a right answer for measuring user satisfaction since the project managers tend to have direct contact to the technology users. Then, the two-item scale was validated by asking the experts in group 2, who are 10 project managers at national laboratories. I found that the project managers have difficulty in providing an answer for the two

4.5.3.2 Measuring the Performance of Mission 2

Success in commercializing a technology can help organizations gain additional revenues (Lichtenthaler, 2006b). The revenue generation rate can thus be a criterion to evaluate the NLS' success in mission 2. However, the pilot test revealed that for the revenue generation rate to be an appropriate measure of success in mission 2, this study needed to control for the size of the project group, as well as for external factors such as the size of the targeted LTUs, many other attributes of the receiving LTUs and the mechanisms for technology transfer. To control for these factors, I used the probability of successfully commercializing a technology that is under development in the project as the performance measure for mission 2.¹⁵ (Please see question 40 in appendix B of this dissertation.) The output variable that is associated with this performance measure is henceforth referred to as OV2.

questions that pertain to the degree of user satisfaction with their projects. However, they were able to provide an answer as to whether or not their targeted customers (who are the LTUs in this dissertation) plan to have a follow-on project or a new project with their project groups. I consequently reduced the two-item scale to measure user satisfaction into a one-item scale and integrated it into the questionnaire for project managers.

¹⁵ In section 2.1.2, I had argued two points. First, a project group can generate revenue before the start of a project via a grant or through contract research. Second, a project group can generate revenue after the completion of a project through licensing, consulting and training. Thus, I had originally proposed one item that was based on objective data (please see question 8 in appendix B of Ploykitikoon, 2012), and a two-item Likert scale as a proxy measure for assessing the performance of mission 2 (please see questions 49 and 50 in appendix B of Ploykitikoon, 2012). During the pilot test, I validated the questions with the experts from group 2 and group 3. I found that the revenue generated from research and development projects tended to depend on not only the size of the project group but also on other external factors. These external factors included type of the targeted customers, sizes of the targeted customers and type of mechanism for transferring technology. For example, technological knowledge developed by a project group can create \$1M in revenue when it is transferred to a large-size private company or a government agency, which is willing to get exclusive right over the technology. In contrast, similar technological knowledge is likely to generate only \$0.1M, if it is commercialized for small companies. To control the impact of these and other external factors on the success of project groups in technology commercialization, I used the probability of successfully commercializing a technology from the project under development as a measure of mission 2. (Please see question 40 in appendix B.)

4.5.3.3 Measuring the Performance of Mission 3

A variety of measures characterized the characterization of mission 3, whose purpose is to generate, retain and sustain a national R&D capability for the future of the country. The most common measure for R&D output is intellectual property (IP) (Siegel, 2004; Agrawal, 2002; Zucker *et al.*, 2002), which can manifest itself in the form of patents or copyrighted publications and has been shown to enhance the national competitiveness (Tong & Frame, 1994; Pavitt, 1998; Furman & Hayes, 2004; Furman *et al.*, 2002; Fagerberg *et al.*, 2007).¹⁶ During the pilot test, I discovered that most of research projects generate zero, one or two publications or patents per project. I consequently proposed two measures for mission 3: the probability that a project would generate a publication and the probability that a project would generate a patent. (Please see question 41 and 42 in appendix B.) The output variables associated with these measures are henceforth respectively referred to as OV3.1 and OV3.2.

The directors of the research programs (the five experts in group 3) pointed me to the third performance for mission 3—versatility of the technology under development. The

¹⁶ Originally, I used the total number of patents, copyrights and publications as a measure of performance for retaining and sustaining national competitiveness in science and technology. However, Pavitt, 1998, contents that IP that is aligned with current and future national goals is more valuable than IP that is not. The degree of alignment of IP with organizational goals can be measured subjectively (Lichtenthaler, 2006b); however, once again, one needs to control for project size. I consequently proposed a two-item scale to assess a project's success in achieving mission 3. One item elicits the relative number of patents, copyrights and publications that the project under study has produced when compared to projects of similar size; the other tries to extract the degree of alignment with the roadmap of the national laboratories. (Please see questions 9.1, 9.2 and 47 of appendix B of Ploykitikoon, 2012.) During the pilot test, I found that the experts had difficulty answering questions pertaining to the number of patents, copyrights and publications that the project under study has produced if the answer was supposed to be normalized for project size. The experts had trouble even when they compared to projects of similar size. It was difficult for them to compare these measures on a Likert scale.

output variable associated with this measure is henceforth referred to as OV3.3. To operationalize this variable, I obtained NSTDA's list of 25 strategic programs for long-term competitiveness, and I asked the project managers to identify as many strategic programs of the national laboratories to which the output of their projects could be applied. (Please see question 3 of appendix B.)¹⁷ The summation score of the strategic programs to which the output of their projects can be applied is used as a measure of the versatility of the technology that projects generate. The experts believed that this measure contributes towards mission 3 — generating, retaining and sustaining the technological capabilities of the national laboratories.

4.5.4 Control Variables

For the control variables, generally, in group studies, there are four variables that influence a project's performance: project size, project resources, project duration and project experience (Ancona & Caldwell, 1992; Edmondson, 1999; MacCormack *et al.*, 2001; Cummings, 2004; Bresman, 2010). Project size is determined by a count of the members of the project group. Project resources are determined by a count of the number of PhD researchers who are expected to play a leading role within the project or play the

¹⁷ In the pilot test with the experts in group 3, I found that these experts had either difficulty answering the degree of alignment with the roadmap of the national laboratories, or they were likely to provide high score for the degree of alignment for each project under their jurisdiction. The experts proposed another way to ask the degree of contribution of a research project to long-term capabilities of national laboratories. I obtained a list of NSTDA'S 25 strategic programs for long-term competitiveness, and I asked project managers to identify as many strategic programs within the national laboratories as possible to which the output of their projects can be applied. (Please see question 3 of appendix B of this dissertation.) The summation score of strategic programs to which the output of their projects can be applied is used as a measure of the versatility of the technology that projects generate. The experts believed that this measure contributes towards the mission 3—generating, retaining and sustaining technological capabilities of national laboratories.

role of technology gatekeeper. This study counts financial resources as an output variable because they reflect project performance as it pertains to mission 2. A project may gain these financial resources from contract research, collaborative research, or research funds from other government agencies. Project duration is given by the number of months from start to finish of the project. Project experience is a function of prior related knowledge, so this study will consider it as a moderating variable.

Machlup (1962 as cited by Godin, 2007) discussed three stages of technology development: 1) research, 2) applied research, and 3) development and demonstration. Each of the 95 laboratories under observation performs projects at which the technology under development is at one of the three stages of maturity defined by Machlup, 1962. I decided to have the respondents identify in the questionnaire the stage of development of the technology that they were working on in their project, because that item could in principle be correlated to performance.

Ease of learning, technological opportunity and appropriability have been shown to be a function of type of technology (W. M. Cohen & Levinthal, 1990). Different technologies may also exhibit different degrees of stickiness (von Hippel, 1994; Szulanski, 1996) and asset specificity (Williamson, 1981), which tend to affect the ability to transfer knowledge and correlate to project performance. The 95 laboratories that were under study are in charge of one and only one of the following different groups of technologies—1) biotechnology; 2) materials and nano-materials; and 3) computer and information technology, which are very different from each other. I consequently decided to have the respondents identify the technology group to which their project

belongs in the questionnaire because that item could in principle be correlated to performance.

4.5.6 Summary of this Section

Table 4.2 summarizes this section. It links the variables of this study as they are defined in figure 3.5 and table 2.3 to the corresponding questions in the validated questionnaire in appendix B. It also shows that all variables were validated by a theoretical review and a pilot test that involved up to 25 experts. Some variables were also corroborated by objective data from the NSTDA database.

Table 4.2: Conclusion of Section on Measurement of Variables in this Dissertation

Variables (Numbers before variables refer to Figure 3.5 and Table 2.3)	Order in questionnaire	Validation
Measuring Independent Variables		
1. Degree of engagement with other R&D projects inside NLS via contextual learning activities (1. CLAs)	Q.11, 15	Ancona and Caldwell, 1992; Bresman, 2010 and pilot test with 20 experts
2. Degree of engagement with other R&D projects inside NLS via vicarious learning activities (2. VLAs)	Q.19,20	Bresman, 2010 and pilot test with 20 experts
3. Degree of engagement with local universities inside NIS via contextual learning activities (3. CLAs)	Q.12, 16	Ancona and Caldwell, 1992; Bresman, 2010 and pilot test with 20 experts
4. Degree of engagement with local universities inside NIS via vicarious learning activities (4. VLAs)	Q.20, 25	Bresman, 2010 and pilot test with 20 experts
5. Degree of engagement with local technology users inside NIS via contextual learning activities (5. CLAs)	Q.14, 18	Ancona and Caldwell, 1992; Bresman, 2010 and pilot test with 20 experts
6. Degree of engagement with local technology users inside NIS via vicarious learning activities (6. VLAs)	Q.22, 23, 27, 28	Bresman, 2010 and pilot test with 20 experts
7. Degree of engagement with international sources outside NIS via contextual learning activities (7. CLAs)	Q.13, 17	Ancona and Caldwell, 1992; Bresman, 2010 and pilot test with 20 experts
8. Degree of engagement with international sources outside NIS via vicarious learning activities (8. VLAs)	Q.21, 25	Bresman, 2010 and pilot test with 20 experts
Measuring Moderating Variables		
9. Degree of prior knowledge	Q.7-Q.10, Q.38	Theoretical review based on e.g. Cohen and Levinthal, 1990; Nemanich <i>et al.</i> , 2010 and pilot test with 20 experts
10. Degree of prior experience	Q.33-Q.3	Theoretical review based on e.g. Allen, 1971; Huber, 1991 and pilot test with 20 experts
11. Degree of project internal learning activities (PILAs)	Q.29-Q.32	Edmondson, 1999, Bresman, 2010 and pilot test with 20 experts
Measuring Control Variables		
Stage of technology development	Q.1	Theoretical review, pilot test with 20 experts and objective data
Types of technology	Q.2	Theoretical review, pilot test with 20 experts and objective data
Total numbers of staff members working on the project under study	Q.4	Theoretical review, pilot test with 20 experts and objective data
Number of staff members working on the project under study with Ph.D. as the highest degree	Q.5	Theoretical review, pilot test with 20 experts and objective data
Measuring Dependent Variables		
Mission 1 (OV1): The degree to which the LTUs are satisfied with the project's performance.	Q.39	Theoretical review based on Spann <i>et al.</i> , 1995 and pilot test with 25 experts
Mission 2 (OV2): The probability that the R&D project will generate revenue for the national laboratories.	Q.40	Theoretical review based on Lichtenthaler, 2006, pilot test with 25 experts and objective data
Mission 3: The degree to which the R&D project contributes to retaining and sustaining tech capabilities:		
Mission 3.1 (OV3.1): The probability that the R&D project will generate at least one publication	Q.41	Theoretical review based on e.g. Pavitt, 1998; Siegel, 2004; Lichtenthaler, 2006, pilot test with 25 experts and objective data
Mission 3.2 (OV3.2): The probability that the R&D project will generate at least one patent	Q.42	
Mission 3.3 (OV3.3): the degree of versatility of projects contributing for retaining and sustaining tech capabilities	Q.3	

4.6 DATA COLLECTION

4.6.1 Obtaining Authorization to Perform the Study

I contacted the director of NSTDA, in order to obtain permission for data collection and to ask for lists of NSTDA's research and development projects. Then, I contacted the directors of the three national institutes within NSTDA that are in charge of the 95 laboratories under study, in order to obtain permission for data collection and to gain access to the lists of research projects that were under their jurisdiction. Upon receiving permission to conduct my research from the institute directors, I contacted **124** project managers via telephone to ask them to participate in this study. One hundred twenty-three out of **124** project managers participated in the study, which amounts to a response rate of more than 99%.

4.6.2 Selection of Projects

Projects were selected according to two criteria:

1. Projects that have been completed within the past two years were included in this study because the managers should be able to recall the details of every recent project for which they were responsible.
2. The sample was limited to R&D projects that varied in size from at least 1.5 to at most 7.0 members as calculated by FTE. This criterion controls for project size.

This yielded a total of 208 projects for the study that fulfill the above project selection criteria.

4.6.3 Administering the Survey

The survey for this research was administered via face-to-face interviews with project managers. I was physically present when the respondents completed the survey. The first part of the survey consisted of a questionnaire that elicited quantitative data and had been validated by a process that has been discussed above. I also conducted unstructured interviews with the respondents about issues that concerned their specific projects. These interviews lasted from 30 to 120 minutes. The qualitative data that was gathered in these interviews was primarily used to interpret the quantitative data from the survey. To ensure confidentiality, the interviews were not recorded on video or audio, but I was allowed to take notes.

4.6.4 The Questionnaire

The validated questionnaire for project managers is presented in detail in appendix B. The questionnaire consists of three parts; general information in appendix B.1; data concerning the sources of knowledge in appendix B.2 and data concerning the project performance in part appendix B.3.¹⁸ Appendix B.1 of the questionnaire for project managers includes 10 questions that collect data for control variables (questions 1, 2, 4, 5 and 6); objective data for moderating variables (questions 7 through 10); and data for one

¹⁸ Appendix B.3 asked the project managers about the expected results of their projects.

dependent variable (OV3.3, question 3). Appendix B.2 consists of 29 items that elicit responses on a Likert scale. This part collects subjective data for independent variables, moderating variables and a dependent variable. The propensity of each project group to engage with external sources of knowledge is measured in questions 11 to 28. Project-internal factors are elicited in questions 29 to 38. The degree of user satisfaction in mission 1 (OV1) is elicited in question 39. Appendix B.3 includes 3 questions concerning the expected results of the projects. Question 40 asks whether the project has generated revenue (OV2). Question 41 asks the respondents to estimate the probability that the project will generate at least one publication in an indexed journal (OV3.1). Question 42 asks the respondents to estimate the probability that the project will generate at least one patent.

Table 4.3 presents the relationships among questions in the questionnaires, research hypotheses, research questions and research gaps of this dissertation.

Table 4.3: Research gaps, research questions, hypothesis and items on the questionnaire

RG.	RQ.	HP.	Items from Conceptual Framework (Figure 2.5)				Questions in appendix B		
			Exogenous Source	Inflow/Internal Mechanism	Critical Mission	Internal Knowledge	Input Variables (App. B)	Moderating Variables (App. B)	Output Variables (Appendix C)
RG-1	RQ-1	1a	ORDU	1. CLAs 2. VLAs	M1	none	Q11,15 Q 19,24	none	Q39
		1b	ORDU	1. CLAs 2. VLAs	M2	none	Q11,15 Q 19,24	none	Q40
		1c	ORDU	1. CLAs 2. VLAs	M3	none	Q11,15 Q 19,24	none	Q3,Q41,Q42
		2a	LocUniv	3. CLAs 4. VLAs	M1	none	Q12,16 Q 20,25	none	Q39
		2b	LocUniv	3. CLAs 4. VLAs	M2	none	Q12,16 Q 20,25	none	Q40
		2c	LocUniv	3. CLAs 4. VLAs	M3	none	Q12,16 Q 20,25	none	Q3,Q41,Q42
		3a	LTUs	5. CLAs 6. VLAs	M1	none	Q14,18 Q 22,23,27,28	none	Q39
		3b	LTUs	5. CLAs 6. VLAs	M2	none	Q14,18 Q 22,23,27,28	none	Q40
		3c	LTUs	5. CLAs 6. VLAs	M3	none	Q14,18 Q 22,23,27,28	none	Q3,Q41,Q42
		4a	InatSrc	7. CLAs 8. VLAs	M1	none	Q13,17 Q 21,26	none	Q39
		4b	InatSrc	7. CLAs 8. VLAs	M2	none	Q13,17 Q 21,26	none	Q40
		4c	InatSrc	7. CLAs 8. VLAs	M3	none	Q13,17 Q 21,26	none	Q3,Q41,Q42
RG-2	RQ-2	5a	InatSrc	7. CLAs 8. VLAs	n/s	9. PrKn	Q13,17 Q 21,26	Q7-Q10,Q38	Q3,Q39-Q42
		5b	LocUniv	3. CLAs 4. VLAs	n/s	9. PrKn	Q12,16 Q 20,25	Q7-Q10,Q38	Q3,Q39-Q42
RG-3	RQ-3	6a	ORDU	1. CLAs 2. VLAs	n/s	10. PrExp	Q11,15 Q 19,24	Q33-Q37	Q3,Q39-Q42
		6b	LocUniv	3. CLAs 4. VLAs	n/s	10. PrExp	Q12,16 Q 20,25	Q33-Q37	Q3,Q39-Q42
		6c	LTUs	5. CLAs 6. VLAs	n/s	10. PrExp	Q14,18 Q 22,23,27,28	Q33-Q37	Q3,Q39-Q42
		6d	InatSrc	7. CLAs 8. VLAs	n/s	10. PrExp	Q13,17 Q 21,26	Q33-Q37	Q3,Q39-Q42
RG-4	RQ-4	7a	InatSrc	7. CLAs 8. VLAs	n/s	11. PILAs	Q13,17 Q 21,26	Q29-Q32	Q3,Q39-Q42
		7b	LocUniv	3. CLAs 4. VLAs	n/s	11. PILAs	Q12,16 Q 20,25	Q29-Q32	Q3,Q39-Q42
		7c	LTUs	5. CLAs 6. VLAs	n/s	11. PILAs	Q14,18 Q 22,23,27,28	Q29-Q32	Q3,Q39-Q42

ORDU = Other Research and Development Units (Groups)

LocUniv = Local Universities (Domestic Engagement)

LTUs = Local Technology Users

InatSrc = International Sources

PrExp = Prior Experience

PrKn = Prior Knowledge

PILAs = Project Internal Learning Activities

obj. = objective data from archives

n/s = not specific to any particular mission

4.7 DATA ANALYSIS

This section discusses the data analysis process. The data from the questionnaire were entered into a spread sheet and subsequently analyzed by the statistical package SPSS. First I generated the descriptive statistics. These were followed by a factor analysis and a correlation matrix. I subsequently generated a series of multiple regression models for all output variables, which I organized in a hierarchical fashion. Data are displayed in tables and in graphs.

4.7.1 Descriptive Statistics

I ran the descriptive statistics to summarize information on the sample. The descriptive statistics can be used to see sample size and distribution of each variable under study. The basic statistics for each variable consist of the sample size, the minimum score, the maximum score, the mean and the standard deviation.

4.7.2 Factor Analysis and Correlation Matrix

This study uses factor analysis to confirm construct validity of measurement after conducting the survey (D. R. Cooper & Emory, 1995) and to reduce the number of variables into a manageable number of meaningful orthogonal factors.¹⁹ If the factors

¹⁹ The meaningful factors confirm construct validity of measurement in this study. Construct validity answers how we measure what we want to measure (Judd et al., 1991, p. 29). In general, we can use item scales from existing literature or develop new item scales based on theoretical review to ensure construct validity before conducting the survey, and we can use factor analysis to confirm construct validity after conducting the survey (D. R. Cooper & Emory, 1995).

that are generated by SPSS align with the hypothesis, then I can be sure that I am measuring what I want to measure (Judd *et al.*, 1991, p. 29). According to Field, 2005, p. 634, "how many factors to extract will depend on why we're doing the analysis in the first place and if you're trying to overcome multi-collinearity problems in regression, then it might be better to extract too many factors than too few." Also, Hair *et al.* (1995) and Field (2005) suggest that to confirm reliability of measurement, Cronbach's alpha coefficient of each construct should be higher than .6 for exploratory factor analysis (Hair *et al.*, 1995; Field, 2005). Therefore, this study extracts the factors by considering the meaning of factors, percentage of the variance explained, and reliability of the construct of each factor.

The factors resulting from factor analysis is used to confirm criterion-related validity of the input factors via correlation analysis. Criterion-related validity measures the degree to which the predictor is adequate in capturing the relevant aspects of the criterion. In addition, we can use correlation analysis to confirm criterion-related validity after conducting the survey (D. R. Cooper & Emory, 1995). The matrix of correlations helps us to assess the degree of interdependence between variables. It can also be used to ascertain whether there is multi-collinearity amongst the predictors (Field, 2005, p. 179).

4.7.3 Regression

To determine the relative impact of the independent variables on the dependent variable, this study uses multiple regression, which is "... an extension of simple regression in which an outcome is predicted by a linear combination of two or more predictor

variables” (Field, 2005, p. 738). I use multiple regression for OV1 and OV3.3, which are measured on a Likert scale. I use logistic regression, “a version of multiple regression in which the outcome is dichotomous” (Field, 2005, p. 736), for output variables OV2, OV3.1 and OV3.2, which measure the odds of whether a particular event occurs or not. The details of my use of multiple regression is given in appendix C.

I use two approaches to regression in this study. In the first approach, I include all predictors in the model. In the second approach, I use the stepwise-backward function of SPSS. I choose the model that explains more of the variance of outcome (the highest adjusted R^2). It turns out that the first approach works better for models that do not include interactions between input variables and moderating variables. Stepwise-backward works better for models that involve interactions between input variables and moderating variables.²⁰

4.7.4 Modified Hierarchical Approach

The main purpose of this dissertation is to address its stated research questions. This can be done by deploying a hierarchical approach to regression, which consists of building a series of regression models that increase in complexity as new variables are added. Hierarchical approaches are considered standard practice for analyzing models with

²⁰ The backward-stepwise method calculates the contribution of each predictor on the outcome by comparing the significance value or the t-test of each predictor against a removal criterion. If a predictor meets the removal criterion or does not improve the prediction power of the model, then it is removed from the analysis. Then the model re-assessed the remaining predictors. Field (2005) also mentioned “the backward method runs lower risk of missing a predictor that predicts the outcome than the forward method” (Field, 2005, pp. 160-161) and it works when the model contains many predictors.

interaction effects (Aiken & West, 1991; J. Cohen *et al.*, 2003, Espinosa *et al.*, 2007). They help us determine whether the explanatory power of a regression model can be augmented by adding additional blocks of variables. A hierarchical approach typically begins with a baseline model that consists of input variables and necessary control variables. Moderating variables are added as a block to determine whether they increase the explanatory power with respect to the baseline. The interactions between input variables and moderating variables are subsequently added as a block to discern any increase in explanatory power with respect to the model that has integrated the input variables and moderating variables.

The research in this dissertation deploys an extended version of a hierarchical approach to regression that allows me to address research questions RQ-1 through RQ-4 and the fundamental research question that has motivated this dissertation. This approach, which requires a total of five regression models per output variable, is depicted in figure 4.2.

Addressing RQ-1 involves a test of hypotheses H.1 through H.4, which pertain to knowledge inflow. This can be achieved by developing a *knowledge inflow baseline* (model 1), which includes input variables and input factors that pertain exclusively to knowledge inflow, in addition to some necessary control variables. The impact of internal sources of knowledge on performance can be assessed by generating an *integrated model* (Model 3), which includes the variables from the knowledge inflow baseline plus a block of moderating variables that pertain to knowledge that resides within or is developed in the various project groups within the national laboratories. If

the total variance explained by the integrated model significantly exceeds that of the baseline model, then the moderating variables have a significant impact on performance.

Table 4.4: Hierarchy of regression models

<u>Factors</u>	<u>Model 1. Knowledge Inflow Baseline</u>	<u>Model 2.1. Project Group Baseline</u>	<u>Model 2.2. Intra- Organization Baseline</u>	<u>Model 3. Integrated Model</u>	<u>Model 4. Interaction Model</u>
Factor of moderating variables (internal knowledge)	Not incl.	Incl.	Incl.	Incl.	Incl.
Factor of independent variables (knowledge inflows)	Incl.	Not incl.	Incl. ORDU only	Incl.	Incl.
Interactions between Factor of moderating variables and Factor of independent variables	Not incl.	Not incl.	Not incl.	Not incl.	Incl.

Research questions RQ-2, RQ-3 and RQ-4, which have given rise to hypotheses H.5, H.6 and H.7, respectively, address issues pertaining to the capacity to absorb knowledge from external sources. Investigating these issues inherently involves studying the interactions between the input variables/factors that pertain to external sources of knowledge and the moderating variables/factors that pertain to internal sources of knowledge. In a hierarchical approach this is best achieved by generating an *interaction model* (model 4) in which a block of variables that represent the interactions between the input variables/factors and the moderating variables/factors are added to the variables/factors that are already in the integrated model.

In order to pursue the primary research question that has motivated this dissertation, I need to determine to what degree engagement with the external sources of knowledge affects the performance of R&D project groups within national laboratories in technological latecomer countries. This requirement calls for a comparison between the magnitude of the impact of knowledge inflows and the magnitude of the impact of knowledge that already exists within or is generated within the various project groups inside national laboratories. To make this comparison, I added an additional regression model to my hierarchy. This *project group baseline* (model 2.1) contains all the variables/factors that pertain to knowledge that is internal to the project group. I compare the total variance explained by this model to the total variance explained by the knowledge inflow baseline. This comparison gives the managers of the national laboratories insight into the relative impact of external and internal knowledge on the performance of R&D project groups. This insight can help managers decide whether to allocate more resources to pursuing new R&D projects as opposed to funding partnerships with external sources of knowledge.

Managers of the national laboratories would also like to gain insight into the impact of collaboration between the various R&D project groups within their organization. I added an additional regression model to my arsenal of models for this purpose. This *intra-organization baseline* (model 4) includes all the variables/factors contained in the project group baseline plus variables/factors pertaining to knowledge inflows from other R&D project groups (ORDUs) within the national laboratories. Managers of the laboratories can assess the impact of collaborative efforts on performance by comparing the total

variance explained by the intra-organization baseline to the total variance explained by the project group baseline.

The impact of external and internal knowledge on performance may vary from mission to mission. For this reason, I ran all five regression models on all on all five output variables. I used normal multiple regression to quantify the impact on user satisfaction, the performance metric for mission 1, and on the versatility of the technology that has been developed, one of three output variables associated with mission 3. I ran logistic multiple regressions to assess the impact on the probability of commercializing a technology, the performance metric for mission 2. I also ran logistic multiple regressions to assess the impact on the probability of generating a publication and the probability of generating a patent. Both these output variables are associated with mission 3. I used the R^2 , the adjusted R^2 and the F-ratio to benchmark the variance explained by and the significance of the regular multiple regressions. I used the Cox & Snell R^2 , the Nagelkerke's R^2 , the chi-square and '% correct' to compare the variance explained by and the significance of the logistic multiple regressions. All of these criteria are described in more detail in appendix C.

5. RESEARCH RESULTS

This chapter presents in five sections the results of the empirical study that has been conducted for this dissertation. After reporting the descriptive statistics in section 5.1, I discuss the results of the factor analysis and the correlation matrix in section 5.2. Section 5.3 compares the various regression models that I have run for the purpose of data analysis. Section 5.4 the findings that pertains to research question RQ-1 (hypotheses 1 through 4). The final section (5.5) covers research questions RQ-2, RQ-3 and RQ-4 (hypotheses 5, 6 and 7, respectively). It discusses results that concern interactions between factors pertaining to knowledge inflows and factors pertaining to project-internal knowledge.

5.1 DESCRIPTIVE STATISTICS

This section discusses the descriptive statistics of the most important variables of this study. Tables 5.1 through 5.7 display these descriptive statistics on a line-by-line basis. Every line in these tables contains the variable's name, its code, the basic statistics that pertain to the variable, and the corresponding item in the questionnaire in appendix B. This approach allows the reader to trace an individual statistic to the corresponding item in the questionnaire through which data for the statistic has been elicited. All items in table 5.1 through table 5.7 exhibit sufficient variability to enable further statistical analysis.

Table 5.1: General information about projects in the national laboratories

	Code	N	Min	Max	Mean	Std. Dev.	Questions' order in questionnaire
Project ID	Project ID						
Basic research	Basic_stg.	208	0	1	.13	.342	Q.1 R&D strategy: Please classify the project by stage of technological development by using the definitions from below.
Applied research	App_stg.	208	0	1	.25	.437	
Development and demonstration	DD_stg.	208	0	1	.62	.488	
Bio technology	Bio_tech.	208	0	1	.28	.450	Q.2 Please classify the project by technology type.
Material and Nano technology	MN_tech.	208	0	1	.36	.481	
Computer and software technology	ES_tech.	208	0	1	.36	.481	
Number of project group members	NO_mem	208	1.5	7.0	2.319	.597	Q.4 Number of full-time members working on this project
Number of PhD in project group	NO_PhD	208	.0	5.0	1.538	1.133	Q.5 Number of full-time members working on this project with Ph.D. as the highest degree
Number of MSc in project group	NO_MSc	208	.0	7.0	1.793	1.319	Q.6 Number of full-time members working on this project with Masters as the highest degree

Table 5.1 provides general information about the projects in the national laboratories. These include the development stage of the project and the technology group to which the project belongs. However, the sample size was not large enough to draw any conclusions that were specific the technology group or stage of development. Table 5.1 also displays data pertaining to project staffing and the level of education of the staff that works on the project.

Table 5.2: Descriptive Statistics Pertaining to Output Variables

	Code	N	Min	Max	Mean	Std. Dev.	Questions' order in questionnaire
Mission 1: User Satisfaction	OV1_Sat_LTUs	194	1.0	6.0	3.982	1.510	Q.39 Based on the results of this project, do you think that the targeted customers of this project will have another collaborative project with your project group in the near future?
Mission 2: Probability of Commercialization of Technology	OV2_Prob_Rev	208	.00	1.00	.476	.501	Q.40 Has any income (in kind or in cash) resulted from this project? And, is any income expected to result from this project?
Mission 3.1: Probability of Generating Publication	OV3.1_Prob_JrPub	208	.0	1.0	.322	.468	Q.41 Have any publications in peer-reviewed journals resulted from this project? Have you submitted any manuscripts for publication in peer-reviewed journals? And, do you expect this project to yield any publications in peer-reviewed journals?
Mission 3.2: Probability of Generating Intellectual Property	OV3.2_Prob_Patent	208	.00	1.00	.375	.485	Q.42 Did any patents result from this project? Have you filed for any patents that are based on work that was conducted for this project? And, do you expect this project to yield any patents?
Mission 3.3: Versatility of Technology	OV3.3_Ver_Tech	208	.0	14.0	2.370	1.712	Q.3 Please identify as many strategic programs of NSTDA as possible, to which the output of this project can be applied.

Table 5.2 summarizes the descriptive statistics that pertain to the output variables for all critical missions. The results for mission 1 show that the project managers tend to agree that, on average, their targeted local technology users are somewhat satisfied with the collaborative efforts between the users and projects within the national laboratories. (The

lower sample size of 194 samples for OV1 results from respondents not being able to answer all questions in the survey.) As for mission 2, the descriptive statistics show that 47.6% of all projects in the sample were able to commercialize at least one technology over the two-year period that preceded the survey. The NSTDA database validates this conclusion.

The scores for the output variables for mission 3 suggest that a substantial effort was being put into developing a long-term R&D capability. At least one publication (journal article with citation index, Q.41.1-41.3) was expected from 32.2 % of all projects that were completed within the two-year period that preceded the survey, and at least one item of patent was expected from 37.5% of all projects over the two-year period that preceded the survey. Finally, the mean score of 2.37 means a project that has been completed within the last two years should yield technology that can be applied in between 2 to 3 technologies on average. This score comes from multiple choices for industry applications in up to 20 strategic programs (strategic program 'a' to 't' as described in appendix B). In this dissertation, the number of strategic programs, in which the output of the project can be applied, is translated into an ordinal scale for further statistical analysis (see appendix D).

Table 5.3: Descriptive Statistics Pertaining to Contextual Learning Activities

	Code	N	Min	Max	Mean	Std. Dev.	Questions' order in questionnaire
Contextual learning with other R&D units 1	IV1_ORDU_CLA1	208	1.0	6.0	1.875	1.0918	Q.11 At least some members of our project group looked for technical ideas in internal reports inside NSTDA.
Contextual learning with local universities 1	IV2_LocUniv_CLA1	208	1.0	6.0	2.111	1.1174	Q.12 At least some members of our project group looked for technical ideas in papers, reports and websites published by universities inside Thailand.
Contextual learning with international sources 1	IV3_InatSrc_CLA1	208	1.0	6.0	4.250	1.4159	Q.13 At least some members of our project group looked for technical ideas in papers, reports and websites that were published by foreign universities and foreign-owned companies.
Contextual learning with technology users 1	IV4_LTUs_CLA1	208	1.0	6.0	3.212	1.4657	Q.14 To understand the needs of our targeted customers, at least some members of our project group looked for technical requirements in industry newsletters, bulletins, websites and trade journals.
Contextual learning with other R&D units 2	IV5_ORDU_CLA2	208	1.0	6.0	2.236	1.1619	Q.15 At least some members of our project group looked for data on what other teams inside NSTDA were doing on similar or complementary projects.
Contextual learning with local universities 2	IV6_LocUniv_CLA2	208	1.0	6.0	2.438	1.1992	Q.16 At least some members of our project group looked for data on what other teams at universities inside Thailand were doing on similar or complementary projects.
Contextual learning with international sources 2	IV7_InatSrc_CLA2	208	1.0	6.0	4.029	1.3483	Q.17 At least some members of our project group looked for data on what other teams at foreign universities and

	Code	N	Min	Max	Mean	Std. Dev.	Questions' order in questionnaire
							foreign-owned companies were doing on similar or complementary projects.
Contextual learning with technology users 2	IV8_LTUs_CLA2	208	1.0	6.0	3.250	1.5180	Q.18 At least some members of our project group looked for data on what our targeted customers were doing on similar or complementary projects.

Table 5.3 explains descriptive statistics pertaining to contextual learning activities (CLAs). The questions regarding contextual learning activities with the four main sources of knowledge are measured in 6-point Likert Scale (see appendix B). The sources of knowledge include other R&D project groups within laboratories (ORDU); local sources of knowledge such as LTUs and local universities (Loc_Univ); and international sources of knowledge (InatSrc) such as foreign universities and foreign-owned companies. The results show that the score for contextual learning activities with international sources of knowledge is high on average, whereas the score for contextual learning activities with local universities and other R&D units within the national laboratories is low on average. In particular, on average, the score for looking for new ideas in internal reports produced by other project groups within the national laboratories is rather low. For example, on average the project groups engage in contextual learning with international sources 1 ($M = 4.250$, $SE = .098$), significantly greater than other R&D project groups within laboratories 1 ($M = 1.875$, $SE = .076$, $t(207) = 18.72$, $p < .001$); local universities 1 ($M = 2.111$, $SE = .077$, $t(207) = 18.26$, $p < .001$) and LTUs1 ($M = 3.21$, $SE = .101$, $t(207) = 7.76$, $p < .001$).

Table 5.4: Descriptive Statistics Pertaining to Vicarious Learning Activities

	Code	N	Min	Max	Mean	Std. Dev.	Questions' order in questionnaire
Vicarious learning with other R&D units 1	IV9_ORDU_VLA1	208	1.0	6.0	2.531	1.436	Q.19 Experts within NSTDA talked to our project group about the lessons learned from their past experiences.
Vicarious learning with local universities 1	IV10_LocUniv_VLA1	208	1.0	6.0	2.543	1.375	Q.20 Experts from universities inside Thailand talked to our project group about the lessons learned from their past experiences.
Vicarious learning with international sources 1	IV11_InatSrc_VLA1	208	1.0	6.0	2.005	1.309	Q.21 Experts from foreign universities and foreign-owned companies talked to our project group about the lessons learned from their past experiences.
Vicarious learning with production units 1	IV12_LTUsPU_VLA1	208	1.0	6.0	3.053	1.754	Q.22 Our targeted customers who have production units talked to our project group about how to develop technology that is suitable for their requirements.
Vicarious learning within end users 1	IV13_LTUsEU_VLA1	208	1.0	6.0	2.817	1.547	Q.23 Our targeted customers who are end users talked to our project group about how to develop technology that is suitable for their requirements.
Vicarious learning with other R&D units 2	IV14_ORDU_VLA2	208	1.0	6.0	2.519	1.411	Q.24 At least some members of our project group talked to experts within NSTDA about lessons learned from our past experiences.
Vicarious learning with local universities 2	IV15_LocUniv_VLA2	208	1.0	6.0	2.606	1.369	Q.25 At least some members of our project group talked to experts within universities inside Thailand about lessons learned from our past experiences.
Vicarious learning with international sources 2	IV16_InatSrc_VLA2	208	1.0	6.0	2.077	1.205	Q.26 At least some members of our project group talked to experts from foreign universities

	Code	N	Min	Max	Mean	Std. Dev.	Questions' order in questionnaire
							and foreign-owned companies about lessons learned from our past experiences.
Vicarious learning with production units 2	IV17_LTUsPU_VLA2	208	1.0	6.0	3.216	1.798	Q.27 At least some members of our project group talked to our targeted customers who have production units to determine ways to improve our project.
Vicarious learning with end users 2	IV18_LTUsEU_VLA2	208	1.0	6.0	3.053	1.677	Q.28 At least some members of our project group talked to our targeted customers who are end users to determine ways to improve our project.

Table 5.4 depicts the descriptive statistics pertaining to vicarious learning activities (VLAs). The questions regarding vicarious learning activities with the four main sources of knowledge are measured in 6-point Likert Scale (see appendix B). The sources of knowledge include knowledge inflows from other R&D project groups within laboratories (ORDU), local universities (Loc_Univ), international sources of knowledge (InatSrc), and local sources of knowledge LTUs. The study also classifies vicarious learning activities with LTUs into two types: vicarious learning with LTUs who have production units and vicarious learning with LTUs who are end users.

The results in table 5.4 suggest that the project groups within the national laboratories, on average, tend not to pursue vicarious learning very aggressively with any external source of knowledge. The mean for all scores for vicarious learning was below the midpoint of 3.5.

Table 5.5: Descriptive Statistics Pertaining to Prior Knowledge

	Code	N	Min	Max	Mean	Std. Dev.	Questions' order in questionnaire
Prior knowledge in core technology	MV1_PrKn_Core	208	1.0	6.0	4.971	1.7581	Q.7 How long was your group developing technology that is directly relevant or useful to this project?
Prior knowledge in journal publications	MV2_PrKn_Jr	208	1.0	6.0	2.156	1.8286	Q.8 How many journal publications that were directly relevant or useful to this project did your project group generate before this project began?
Prior knowledge in patents	MV4_PrKn_Pat	208	1.0	6.0	1.611	1.2384	Q.10 How many patents that were directly relevant or useful to this project did your project group generate before this project began?
Prior knowledge level of project group	MV14_PrKn_Lev	208	1.0	6.0	2.904	1.5504	Q.38 Prior to the start of our project, our project group generated a lot of patents and publications that are relevant to this project.

Table 5.5 presents the descriptive statistics that pertain to prior knowledge (PrKn), which is considered a type of internal knowledge in this study. Three of the four questions regarding prior knowledge (Q.7, Q.8, and Q.10 in appendix B) are also measured in ordinal scale, and the other (Q.38 in appendix B) is measured on a 6-point Likert Scale. Knowledge gained before the project starts is measured in a variety of forms including years of experience in developing the core technology (PrKn_Core), number of cumulative journal publications (PrKn_Jr), number of cumulative patents (PrKn_Pat), and the perspective of project managers on knowledge level of their project groups (PrKn_Lev). The results show that on average the score for PrKn_Core ($M = 4.971$, $SE = .1219$), is significantly higher than the scores for cumulative journal publications ($M = 2.156$, $SE = .1268$, $t(207) = 18.64$, $p < .001$), total number of patents ($M = 1.611$, $SE =$

.0859, $t(207) = 24.44$, $p < .001$), and the managers' rating of prior knowledge ($M = 2.904$, $SE = .1075$, $t(207) = 15.18$, $p < .001$). This result underlines the importance of PrKn_Core in NLS.

Table 5.6: Descriptive Statistics Pertaining to Project-Internal Learning Activities

	Code	N	Min	Max	Mean	Std. Dev.	Questions' order in questionnaire
Project-internal learning activity 1	MV5_PILA1	208	1.0	6.0	4.125	1.144	Q.29 Our project group took time to figure out ways to improve our work process.
Project-internal learning activity 2	MV6_PILA2	208	1.0	6.0	4.298	1.045	Q.30 Our project group took time to monitor our project's work progress.
Project-internal learning activity 3	MV7_PILA3	208	2.0	6.0	4.320	1.040	Q.31 Individuals within our project group spoke up to challenge technical assumptions concerning issues that were under discussion among members of our project group.
Project-internal learning activity 4	MV8_PILA4	208	2.0	6.0	4.442	1.009	Q.32 The project group implemented suggestions made by team members.

Table 5.6 presents descriptive statistics pertaining to project-internal learning activities (PILAs). The questions regarding PILAs are measured in 6-point Likert Scale (see Q.29-32 in appendix B). PILAs include taking time to figure out ways to improve work process of the project (PILA1), taking time to monitor project's work progress (PILA2), speaking up of project members to challenge technical assumptions concerning issues that were under discussion among members of the project group (PILA3) and implementation of suggestions made by team members (PILA 4). The results show that the scores for the questions regarding PILAs in the sample are high on average. This suggests that the

project managers tend to believe that there is a high degree of interaction among members of their project groups.

Table 5.7 presents descriptive statistics pertaining to prior experience (PrExp), another type of internal knowledge. This study classifies prior experiences of the project groups into five categories and measures them on a 6-point Likert Scale. Prior experience constitutes either advanced education or work experience. The results presented in table 5.7 underscore that, on average, project managers believe that their project groups contain many individuals with a prior advanced education experience that is relevant to the R&D project. This advanced education may have taken place at international sources of knowledge (foreign universities) or domestic sources of knowledge (local universities). In contrast, the results indicate that the scores for the questions regarding working experiences in the sample are slightly low on average. This suggests that the project managers tend to believe that there is a slightly low degree of work experience at external sources of knowledge among members of their project groups.

A t-test of the pertinent variables shows that project managers believe that prior education on relevant subject matter was more common than relevant prior work experience. For example, relevant prior education at local universities (Q.34; $M = 4.476$, $SE = 1.054$) scored significantly higher than prior work experience at international sources of knowledge (Q.35; $M = 3.024$, $SE = 1.73$, $t(207) = 10.76$, $p < .001$), at local technology users (Q.36; $M = 3.32$, $SE = 1.86$, $t(207) = 8.53$, $p < .001$) and at other R&D units within the national laboratories (Q.37; $M = 3.26$, $SE = 1.63$, $t(207) = 9.94$, $p < .001$). Also, relevant prior education at foreign universities (Q.33; $M = 4.423$, $SE = .113$) scored

significantly higher than prior work experience at international sources of knowledge (Q.35; $M = 3.024$, $SE = .119$, $t(207) = 11.15$, $p < .001$), at local technology users (Q.36; $M = 3.32$, $SE = .129$, $t(207) = 6.69$, $p < .001$) and at other R&D units within the national laboratories (Q.37; $M = 3.26$, $SE = .113$, $t(207) = 7.08$, $p < .001$).

Table 5.7: Descriptive Statistics Pertaining to Prior Experience

	Code	N	Min	Max	Mean	Std. Dev.	Questions' order in questionnaire
Prior experience in education from international sources of knowledge	MV9_PrExp_Ed_InatSrc	208	1.0	6.0	4.423	1.628	Q.33 At least one of our project group members has had very extensive educational experience at a foreign university on subject matter that is relevant to this project.
Prior experience in education from local sources of knowledge	MV10_PrExp_Ed_LocUniv	208	1.0	6.0	4.476	1.054	Q.34 At least one of our project group members had very extensive educational experience at a domestic university on subject matter that is relevant to this project.
Prior experience in working from international sources of knowledge	MV11_PrExp_Wk_InatSrc	208	1.0	6.0	3.024	1.729	Q.35 At least one of our project group members had very extensive working experience abroad on subject matter that relevant to this project.
Prior experience in working with local technology users	MV12_PrExp_Wk_LTUs	208	1.0	6.0	3.317	1.859	Q.36 At least one of our project group members had very extensive working experience with our targeted customers on subject matter that is relevant to this project.
Prior experience in working with other R&D units	MV13_PrExp_Wk_ORDU	208	1.0	6.0	3.260	1.629	Q.37 At least one of our project group members had very extensive working experience with other projects within NSTDA on subject matter that is relevant to this project.

In summary, the descriptive statistics show that, on average, the project managers of R&D project groups in NLTs in TLTs believe that their project groups engage with international sources of knowledge via contextual learning. They scan for ideas for their projects and for data on what other teams were doing on similar or complementary projects. They also rely on internal knowledge gained from project-internal learning activities and the prior education experiences of their team members to complete their R&D projects. In contrast, the project managers believe that the degree of engagement with external sources of knowledge via vicarious learning activities and the degree of internal knowledge gained from the prior work experience of the team members is not very high.

5.2 CORRELATION MATRIX AND FACTOR ANALYSIS

This section presents the results of the correlation analysis of the variables under study and the factor analysis. The correlation analysis for all variables under study is presented in appendix E. Factor analysis has been used to cluster the input variables pertaining to knowledge inflows and the moderating variables pertaining to internal knowledge. A correlation analysis is subsequently performed on the output variables and the factors that emerge from the factor analysis.

In general, a rule of thumb for factor analysis, which is easily learned, easily applied and used as a default in SPSS, suggests that factors with an eigenvalue greater than or equal to 1 can be included in the analysis (Kaiser, 1960). This rule is accurate or reliable when the number of variables in the analysis is lower than 30 variables and the sample size is

higher than 250 (Jolliffe, 1972, 1986; J. P. Stevens, 1992). Some researchers also suggest to include factors above the point of inflexion in the scree plot (Cattell, 1966; Jolliffe, 1972, 1986; J. P. Stevens, 1992). Others stress that it is important to consider the meaning of the factors after extraction (Dunteman, 1989, pp. 22-23; Field, 2005, p. 630; Nardo *et al.*, 2005, p. 21; R. A. Johnson & Wichern, 2007, p. 444) and internal consistency of factors (Hair, *et al.*, 1995; Field, 2005). In some instances, it may be necessary to extend the factor analysis to the point where 80% to 90% of the variance is explained (Dunteman, 1989, pp. 22-23; Nardo *et al.*, 2005, p. 21; R. A. Johnson & Wichern, 2007, p. 444). This will result in the emergence of some factors with little explanatory power. However, these factors cannot be ignored because they may have a strong and highly significant impact on the criterion.

This dissertation wants to include all of sources of knowledge that are potentially critical for a national laboratory in a technological latecomer country in the analysis. Thus, this study follows a guideline of stopping rules for factor analysis suggested by Dunteman, 1989, pp. 22-23; Nardo *et al.*, 2005, p. 21; and R. A. Johnson & Wichern, 2007, p. 444, in which 90% of the variance is explained. When this rule is applied to the dataset that has been collected for this dissertation, the factors that emerge from the factor analysis when 90% of the variance is explained are meaningful and interpretable in real world practice (Dunteman, 1989, pp. 22-23; Field, 2005, p. 630; Nardo *et al.*, 2005, p. 21; R. A. Johnson & Wichern, 2007, p. 444).

Table 5.8 displays the results of the factor analysis and the total variance explained by the analysis. A total of 17 input factors, which explain 90% of the variance, have been

identified. The factors can be classified into two groups: factors pertaining to input variables (FIVs) and factors pertaining to moderating variables (FMVs). The former group results from clustering variables pertaining to knowledge inflows, whereas the latter group results from clustering variables pertaining to internal knowledge. Appendix F illustrates which variables comprise which factors.

SPSS has identified a total of nine FIVs. Four of these are associated with contextual learning activities: the degree of engagement with other R&D project groups via CLAs [FIV8_ORDU_CLAs, $\alpha = .760$]; the degree of engagement with local universities via CLAs [FIV9_LocUniv_CLAs, $\alpha = .723$]; the degree of engagement with international sources via CLAs [FIV6_InatSrc_CLAs, $\alpha = .816$]; and the degree of engagement with LTUs via CLAs [FIV7_LTUs_CLAs, $\alpha = .769$]. The five remaining factors are associated with vicarious learning activities: the degree of engagement with other R&D project groups via VLAs [FIV5_ORDU_VLAs, $\alpha = .867$]; the degree of engagement with local universities via VLAs [FIV3_LocUniv_VLAs, $\alpha = .891$]; the degree of engagement with international sources via VLAs [FIV2_InatSrc_VLAs, $\alpha = .859$]; the degree of engagement via VLAs with local technology users that have production units [FIV1_LTUsPU_VLAs, $\alpha = .946$]; and the degree of engagement via VLAs with LTUs that are end users [FIV4_LTUsEU_VLAs, $\alpha = .916$].

SPSS has identified a total of eight FMVs. One factor pertains to project-internal learning activities [FMV1_PILAs, $\alpha = .887$]. Two factors are associated with prior knowledge: [FMV2_PrKn_PJ, $\alpha = .773$] covers subject matter pertaining to the context of the project, whereas [FMV5_PrKn_Core] measures prior knowledge about the core technology. Five

factors pertain to prior experience, including prior experience in working with other R&D units [FMV4_PrExp_Wk_ORDU]; prior experience in working at international sources of knowledge [FMV8_PrExp_Wk_InatSrc]; prior experience in working with local technology users [FMV3_PrExp_Wk_LTUs]; prior experience in education at local universities [FMV6_PrExp_Ed_LocUniv]; and prior experience in education from international sources of knowledge [FMV7_PrExp_Ed_InatSrc], *i.e.* foreign universities.

Table 5.8 shows that no truly dominant factor or small group of factors explains most of the variation. PILA is the most significant factor; the next five factors pertain to vicarious learning activity. These vicarious learning factors are followed by a group of five factors that are either associated with contextual learning or prior knowledge about the subject matter. The list of factors is closed out by six single variables that are either associated with prior experience of various kinds or prior knowledge about the core technology that is under development.

In summary, the factor analysis identifies 17 factors, which include all input variables and moderating variables under study. The input factors are orthogonal, which means mutually independent, non-redundant and non-overlapping. There is no collinearity between any of the factors, which helps overcome multi-collinearity problems in a regression (Field, 2005). The constructs of the first 11 factors are also reliable with Cronbach's alpha always being greater than 0.7. The last six factors report no Cronbach's alpha since they are individual variables.

Table 5.8: Factor Analysis and Cumulative Variance Explained

Factor #	Initial Eigenvalues		Rotation Sums of Squared Loadings		Factors of Moderating Variables (FMV) and Factors of Independent Variables (FIV)	Description	Cronbach's Alpha
	% of Variance	Cumulative %	% of Variance	Cumulative %			
1	16.212	16.212	10.383	10.383	[FMV1_PILAs]	FMV1: Project internal learning activities	($\alpha = .887$)
2	14.298	30.510	7.005	17.389	[FIV1_LTUsPU_VLAs]	FIV1: Engage with LTUsPU via VLAs	($\alpha = .946$)
3	11.461	41.972	6.678	24.067	[FIV2_InatSrc_VLAs]	FIV2: Engage with InatSrc via VLAs	($\alpha = .859$)
4	7.003	48.975	6.525	30.592	[FIV3_LocUniv_VLAs]	FIV3: Engage with LocUniv via VLAs	($\alpha = .891$)
5	6.306	55.281	6.445	37.037	[FIV4_LTUsEU_VLAs]	FIV4: Engage with LTUsEU via VLAs	($\alpha = .916$)
6	5.325	60.605	6.435	43.473	[FIV5_ORDU_VLAs]	FIV5: Engagement with ORDU via VLAs	($\alpha = .867$)
7	4.535	65.140	5.827	49.299	[FIV6_InatSrc_CLAs]	FIV6: Engage with InatSrc via CLAs	($\alpha = .816$)
8	4.091	69.231	5.743	55.043	[FMV2_PrKn_PJ]	FMV2: Prior knowledge about the subject matter pertaining to the project	($\alpha = .773$)
9	3.358	72.590	5.295	60.337	[FIV7_LTUs_CLAs]	FIV7: Engage with LTUs CLAs	($\alpha = .769$)
10	3.184	75.774	5.215	65.553	[FIV8_ORDU_CLAs]	FIV8: Engagement with ORDU_CLAs	($\alpha = .760$)
11	2.866	78.640	5.061	70.613	[FIV9_LocUniv_CLAs]	FIV9: Engage with LocUniv via CLAs	($\alpha = .723$)
12	2.336	80.976	3.587	74.200	[FMV3_PrExp_Wk_LTUs]	FMV3: Prior experience in working with local technology users	-
13	2.225	83.201	3.504	77.704	[FMV4_PrExp_Wk_ORDU]	FMV4: Prior experience in working with other R&D units	-
14	1.983	85.184	3.353	81.057	[FMV5_PrKn_Core]	FMV5: Prior knowledge in core technology	-
15	1.832	87.016	3.322	84.379	[FMV6_PrExp_Ed_LocUniv]	FMV6: Prior experience in education from local sources of knowledge	-
16	1.668	88.684	3.287	87.666	[FMV7_PrExp_Ed_InatSrc]	FMV7: Prior experience in education from international sources of knowledge	-
17	1.494	90.178	2.042	89.708	[FMV8_PrExp_Wk_InatSrc]	FMV8: Prior experience in working at international sources of knowledge	-

Table 5.9: Correlation Matrix

	Output Variable / Factor	OV1	OV2	OV3.1	OV3.2	OV3.3
Output variables	OV1_Sat_LTUs	1.000				
	OV2_Prob_Rev	.580***	1.000			
	OV3.1_Prob_JrPub	-.206**	-	1.000		
	OV3.2_Prob_Patent	-0.077	-.162*	.167*	1.000	
	OV3.3_Ver_Tech	-0.061	-0.123	.224**	0.050	1.000
Factor of moderating variables (internal knowledge)	FMV1_PILAs	0.081	0.025	0.016	0.024	0.113
	FMV2_PrKn_PJ	-0.033	-0.088	.281***	-0.121	0.065
	FMV3_PrExp_Wk_LTUs	.223***	.272***	-0.071	-.182**	0.066
	FMV4_PrExp_Wk_ORDU	-0.017	0.128	-0.065	0.021	-0.059
	FMV5_PrKn_Core	.140*	0.110	.146*	0.094	0.077
	FMV6_PrExp_Ed_LocUniv	0.100	0.029	-0.025	0.087	-0.034
	FMV7_PrExp_Ed_InatSrc	-0.041	-0.048	0.005	0.080	0.032
	FMV8_PrExp_Wk_InatSrc	-0.053	-0.007	.141*	0.005	.212***
Factor of independent variables (knowledge inflows)	FIV1_LTUsPU_VLAs	.446***	.550***	-.189**	-0.050	-0.096
	FIV2_InatSrc_VLAs	-0.097	-0.078	.192**	-0.119	.168*
	FIV3_LocUniv_VLAs	-0.037	0.016	.183**	0.052	0.066
	FIV4_LTUsEU_VLAs	.371***	.274***	-.213**	0.008	0.086
	FIV5_ORDU_VLAs	-0.051	-.171*	.162*	0.113	.150*
	FIV6_InatSrc_CLAs	0.017	-0.033	.232**	0.075	.135*
	FIV7_LTUs_CLAs	.298***	0.110	-0.046	0.064	-0.077
	FIV8_ORDU_CLAs	-0.044	0.019	0.038	0.024	.149*
	FIV9_LocUniv_CLAs	0.107	0.048	0.041	-0.006	-0.095

*** Correlation is significant at the p<0.001 level (2-tailed).
 ** Correlation is significant at the p<0.01 level (2-tailed).
 * Correlation is significant at the p<0.05 level (2-tailed).
 Correlation is significant at the p≥0.05 level (2-tailed).

Positive	Negative
***	***
**	**
*	*

Table 5.9 presents the correlation matrix of the 17 input factors and the five output variables. Due to the orthogonality of factors, the interactions between all input and moderating variables equal zero and are thus not displayed in table 5.9. The matrix confirms criterion-related validity of the input factors. For example, user satisfaction (OV1_Sat_LTUs) has significantly positive correlations to all factors pertaining to LTUs, but has significantly negative correlation to probability of generating a publication (OV3.1_Prob_JrPub). This shows that the input factors are adequate for capturing the relevant aspects of output variables.

5.3 COMPARING REGRESSION MODELS

This section presents the results of regression analyses that investigate the relative impact of internal and external sources of knowledge on the performance of the national laboratories. Five regression models have been built for each output variable. Model 1, the knowledge inflow baseline, includes factors from outside the project group, only. Model 2.1, the project group baseline, contains factors from inside the project group, only. Model 2.2, the intra-organization baseline, includes factors from inside the national laboratories, i.e., project internal factors and factors pertaining to external learning from other R&D project groups. Model 3, the integrated model, covers all factors from model 1 and 2.1. Model 4, the interaction model, includes almost²¹ all factors from model 1 and model 2, as well as their interactions.

The predictive power of all models for all output variables is summarized in table 5.10. The summary statistics of the models for each output variable are given in appendix G.1 through G.5. Appendix G.1 presents regression results for mission 1 (OV1) -- user satisfaction. Appendix G.2 summarizes regression results for mission 2 (OV2) -- the probability of commercialization. Appendixes G.3 to G.5 respectively display regression results for the output variables that pertain to mission 3: probability of publication (OV3.1); probability of generating a patent (OV3.2); and versatility of technology (OV3.3).

²¹ The interaction model does not cover FIV8, contextual learning about other R&D project groups within the national laboratories; FMV6, prior education at local universities; and FMV7, prior education at foreign universities.

Table 5.10: Summary of Predictive Power of Models 1 through 5 for all Output Variables

Criteria	Model 1. Knowledge Inflow <u>Baseline</u>	Model 2.1. Project Group <u>Baseline</u>	Model 2.2. Intra- Organization <u>Baseline</u>	Model 3. Integrated <u>Model</u>	Model 4. Interaction <u>Model</u>
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Mission-1: User Satisfaction

R ²	.469	.069	.069	.571	.703
R ² adjust	.458	.059	.059	.550	.665
F	41.705***	7.042**	7.042**	27.175***	18.385***
No.	193	193	193	193	193
Δ R ² adjust	-	-	0.000	0.491	0.606

Mission-2: Probability of Commercializing a Technology

Cox & Snell R ²	0.384	0.102	.133	0.485	.604
Nagelkerke's R ²	0.512	0.136	.177	0.648	.807
Chi-square	100.728***	22.419***	29.568***	138.714***	192.909***
Percentage correct	80.3	66.3	69.7	86.1	92.3
No.	208	208	208	208	208
Δ Cox & Snell R ²	-	-	0.031	0.383	0.502
Δ Nagelkerke's R ²	-	-	0.041	0.512	0.671

Mission-3.1: Probability of Generating a Publication

Cox & Snell R ²	0.236	0.115	.141	0.338	0.447
Nagelkerke's R ²	0.329	0.161	.197	0.472	0.625
Chi-square	55.922***	25.390***	31.553***	85.665***	123.321***
Percentage correct	78.8	73.1	74	81.3	86.1
No.	208	208	208	208	208
Δ Cox & Snell R ²	-	-	0.026	0.223	0.332
Δ Nagelkerke's R ²	-	-	0.036	0.311	0.464

Mission-3.2: Probability of Generating a Patent

Cox & Snell R ²	.015	.048	.061	.075	0.237
Nagelkerke's R ²	.020	.065	.083	.102	0.323
Chi-square	3.041	10.199**	13.044**	16.167**	56.182***
Percentage correct	62.5	65.9	63.9	63.9	72.1
No.	208	208	208	208	208
Δ Cox & Snell R ²	-	-	0.013	0.027	0.189
Δ Nagelkerke's R ²	-	-	0.018	0.037	0.258

Mission-3.3: Versatility of Technology

R ²	.091	.058	.102	.149	0.311
R ² adjust	.073	.048	.085	.123	0.25
F	5.099**	6.256**	5.777***	5.857***	5.056***
No.	207	207	207	207	207
Δ R ² adjust	-	-	0.037	0.075	0.202

Note: 1) ΔR² adjust, ΔCox & Snell R² and Δ Nagelkerke's R² are based on model 2.1

- 2) *** Significant at the p<0.001 level (2-tailed).
- ** Significant at the p<0.01 level (2-tailed).
- * Significant at the p<0.05 level (2-tailed).

This study benchmarks the total variance explained and prediction power of each model for all five output variables. The benchmarking criteria include R^2 , Adjusted R^2 , and F-ratio for multiple regressions in mission 1 (OV1) and 3 (OV3.3). In addition, the Cox & Snell R^2 , the Nagelkerke's R^2 , the Chi-Square and the percentage correct are used for benchmarking the prediction power of multiple logistic regressions in missions 2 (OV2) and 3 (OV3.1 and OV3.2) (see appendix C for an explanation of these measures of explanatory power).

Table 5.10 illustrates the results of this exercise. It shows that the five output variables have different predictive power and explanatory power, and that the regression models that include knowledge inflows tend to have greater explanatory power than the ones that do not. I also benchmark the adjusted R^2 , the Cox & Snell R^2 and the Nagelkerke's R^2 , of the intra-organization baseline (model 2.2), the integrated model (model 3) and the interaction model (model 4) to that of the project group baseline (model 2.1). This effort provides an indicator as to how much the inclusion of additional variables improves the predictive and explanatory power of the models.

Output variable OV3.2—the probability of generating at least one item of patent from a project—clearly has the lowest predictive power of all five output variables. The Cox & Snell R^2 and the Nagelkerke's R^2 are below 0.2 for models 1 through 4, meaning that these models cannot explain 20% of the variance. In model 1, the Chi-Square is not significant at the level of $p < 0.05$. This observation suggests that generating a patent is not a strong function of knowledge inflows. Other factors (perhaps economic incentives)

drive the generation of a patent. OV3.2 will henceforth not be used as an indicator for measuring the impact of managing knowledge inflows from various sources on the national laboratories' ability to build a long-term R&D capability for the country.

The remaining output variables -- OV1, OV2, OV3.1 and OV3.3 -- have a relatively high explanatory power, at least for models that involve knowledge inflow. However, models 2.1 and 2.2, which exclude all factors that are exogenous to the national laboratories, have a significantly lower explanatory power. When compared to model 1, models 2.1 and 2.2 are particularly weak indicators of user satisfaction, probability of commercialization and probability of publication. This suggests user satisfaction, commercialization and publication are highly dependent on knowledge inflow into the national laboratories. Not surprisingly, the explanatory power of the regression models increases as more variables are added. Model 3, the integrated model, has a greater explanatory power than models 1, 2.1 and 2.2; model 4, the interaction model, has a greater explanatory power than model 3.

It should be noted that for output variables OV1, OV2, OV3.1 and OV3.3, model 2.2, the intra-organization baseline, is not much of an improvement over model 2.1, the project group baseline. Evidently, including knowledge inflows from other R&D project groups in a regression model does not significantly increase the explanatory power of the model. This implies that the impact of collaborative efforts between R&D project groups within the national laboratories is limited. The national laboratories under study must manage inflows from exogenous sources of knowledge to achieve dramatic improvements in performance.

5.4 THE IMPACT OF KNOWLEDGE INFLOWS

In this section, I present the results that address research question RQ-1: What is the **relative** impact on the performance of national laboratories in latecomer countries of engaging with other project groups within the same organization (hypotheses H.1a, H.1b, H.1c); with local universities (hypotheses H.2a, H.2b, H.2c); with local technology users (hypotheses H.3a, H.3b, H.3c); and with international sources of knowledge (hypotheses H.4a, H.4b, H.4c)? Results cover user satisfaction (mission 1, OV1; hypotheses H.1a, H.2a, H.3a and H.4a); probability of commercializing a technology (mission 2, OV2; Hypotheses H.1b, H.2b, H.3b and H.4b); probability of generating at least one publication (mission 3, OV3.1); and versatility of technology (mission 3, OV3.1). Hypotheses H.1c, H.2c, H.3c and H.4c). I have used the integrated regression model to test the relevant hypotheses, whose results are displayed in appendix G.6. In all of the following hypothesis tests, I use $p < 0.05$ as the threshold for statistical significance.

5.4.1 Engaging with other R&D Project Groups in the National Laboratories²²

Hypothesis 1a for Mission 1: Engagement with other R&D project groups within the NLs has a positive impact on the satisfaction of LTUs.

²² Hypotheses 1a, 1b and 1c pertain to external learning with other R&D project groups in the national laboratories, which are also known as other R&D units or ORDUs. Hypotheses 1a, 1b and 1c respectively pertain to missions 1, 2 and 3.

Hypothesis 1a could not be confirmed (the null hypothesis could not be rejected, $p > .05$). The degree of engagement in external learning activities with other R&D units (project groups) within the national laboratories as a whole does not correlate with statistical significance to user satisfaction. This implies that engagement with other R&D project groups within the NLs has no significant impact on user satisfaction, regardless of whether these learning activities are contextual or vicarious.

Hypothesis 1b for Mission 2: Engagement with other R&D project groups within the NLs has a positive impact on the NLs' ability to generate revenue for themselves by commercializing technology that they have developed.

Hypothesis 1b could not be confirmed (the null hypothesis could not be rejected, $p > .05$) for contextual learning. The degree of engagement in contextual learning activities with other R&D units (project groups) within the national laboratories is not correlated with statistical significance to the probability of commercializing at least one technology from one particular R&D project. This implies that contextual learning activities with other R&D units (project groups) within the national laboratories have no significant impact on commercialization of technology.

Hypothesis 1b has been refuted (the null hypothesis has been rejected, $p = .002$) for vicarious learning. The degree of engagement in vicarious learning activities with other R&D units (project groups) within the national laboratories is inversely correlated to the probability of commercializing at least one technology from a particular project. This

implies that vicarious learning with other R&D units (project groups) has a negative impact on commercialization of technology.

Hypothesis 1c for Mission 3: Engagement with other R&D project groups within NLS has a positive impact on the NLS' ability to build R&D capabilities for the future needs of the country.

Hypothesis 1c could not be confirmed (the null hypothesis could not be rejected, $p > .05$) for contextual learning, if performance is measured by the probability of publication. The degree of engagement in contextual learning activities with other R&D units (project groups) within the national laboratories is not correlated with statistical significance to the probability of generating at least one publication from a particular project. This implies that contextual learning activities with other R&D units (project groups) within the national laboratories have no significant impact on developing a long-term R&D capability of the national laboratories.

Hypothesis 1c has been confirmed (the null hypothesis has been rejected, $p = .023$) for contextual learning with other R&D units (project groups) within the national laboratories, if performance is measured by versatility of technology. The degree of engagement in external learning activities with other R&D units (project groups) within the national laboratories is positively correlated to the versatility of the technology under development. This implies that engaging in contextual learning about other R&D units (project groups) within the national laboratories has a positive impact on the ability to

find additional applications for the technology and should thus enhance the national laboratories' ability to develop a long-term R&D capability.

Hypothesis 1c has been confirmed (the null hypothesis has been rejected, $p = .004$ and $p = .023$) for vicarious learning with other R&D units (project groups) within the national laboratories. The degree of engagement in external learning activities with other R&D units (project groups) within the national laboratories is positively correlated to the probability of generating at least one publication from a particular project and to the versatility of the technology under development in a particular project. This implies that engaging in vicarious learning with other R&D units (project groups) within the national laboratories has a positive impact on the ability to generate publications and the versatility of technology under development. Vicarious learning with other R&D project groups within the national laboratories should thus enhance the national laboratories' ability to develop a long-term R&D capability.

5.4.2 Engaging with Local Universities²³

Hypothesis 2a for Mission 1: Engagement with local universities has a positive impact on the satisfaction of LTUs.

Hypothesis 2a has been confirmed (the null hypothesis has been rejected, $p = .031$) for contextual learning with local universities. The degree of engagement in contextual

²³ Hypotheses 2a, 2b and 2c pertain to external learning with local universities. Hypotheses 2a, 2b and 2c respectively pertain to missions 1, 2 and 3.

learning activities with local universities is positively correlated to user satisfaction. This implies that contextual learning with local universities has a positive impact on user satisfaction.

Hypothesis 2a could not be confirmed (the null hypothesis could not be rejected, $p > .05$) for vicarious learning. The degree of engagement in vicarious learning activities with local universities not is correlated with any statistical significance to user satisfaction. This implies that vicarious learning from local universities has no statistically significant impact on user satisfaction.

Hypothesis 2b for Mission 2: Engagement with local universities has a positive impact on the NLs' ability to generate revenue for themselves by commercializing technology that they have developed.

Hypothesis 2b could not be confirmed (the null hypothesis could not be rejected, $p > .05$) for contextual learning. The degree of engagement in contextual learning activities with local universities is not correlated with statistical significance to the probability of commercializing at least one technology from one particular R&D project. This implies that contextual learning activities with local universities have no statistically significant impact on commercialization of technology.

Hypothesis 2b could not be confirmed (the null hypothesis could not be rejected, $p > .05$) for vicarious learning. The degree of engagement in vicarious learning activities with local universities is not correlated with statistical significance to the probability of

commercializing at least one technology from one particular R&D project. This implies that vicarious learning activities with local universities have no significant impact on commercialization of technology.

Hypothesis 2c for Mission 3: Engagement with local universities has a positive impact on the NLS' ability to build R&D capabilities for the future needs of the country.

Hypothesis 2c has been confirmed (the null hypothesis has been rejected, $p = .001$) for external learning as a whole, when performance is measured by the probability of publication. The degree of engagement in external learning activities with local universities is positively correlated to the probability of generating at least one publication from a particular project. This implies that engaging in external learning activities with local universities has a positive impact on the ability to generate publications. Engaging in external learning activities with local universities should thus enhance the national laboratories' ability to develop a long-term R&D capability.

Hypothesis 2c could not be confirmed (the null hypothesis could not be rejected, $p > .05$) for external learning, if performance is measured by versatility of technology. The degree of engagement in external learning activities with local universities is not correlated with statistical significance to the versatility of the technology that is under development within one particular R&D project. This implies that external learning activities with local universities have no statistically significant impact on versatility of technology.

5.4.3 Engaging with Local Technology Users²⁴

*Hypothesis 3a for Mission 1: Engagement with local users has a **positive** impact on the satisfaction of LTUs.*

Hypothesis 3a has been confirmed (the null hypothesis has been rejected, $p < .001$) for external learning with local technology users with production units. The degree of engagement in external learning activities with local technology users that have production units is positively correlated to user satisfaction, regardless of whether these learning activities are contextual or vicarious. This implies that external learning with local technology users that have production units has a positive impact on user satisfaction.

Hypothesis 3a has been confirmed (the null hypothesis has been rejected, $p < .001$) for vicarious learning with local technology users that are end users. The degree of engagement in vicarious learning activities with local technology users that are end users is positively correlated to user satisfaction. This implies that vicarious learning with local technology users that are end users has a positive impact on user satisfaction.

*Hypothesis 3b for Mission 2: Engagement with local users has a **positive** impact on the NLs' ability to generate revenue for themselves by commercializing technology that they have developed.*

²⁴ Hypotheses 3a, 3b and 3c pertain to external learning with local technology users. Hypotheses 3a, 3b and 3c respectively pertain to missions 1, 2 and 3.

Hypothesis 3b could not be confirmed (the null hypothesis could not be rejected, $p > .05$) for contextual learning about local technology users. There was no statistically significant correlation between the degree of engagement in contextual learning activities with local technology users and the probability of commercializing at least one technology from a particular project. This implies that engaging in contextual learning activities with local technology users has no significant impact on commercialization of technology.

Hypothesis 3b has been confirmed (the null hypothesis has been rejected, $p < .001$) for vicarious learning with local technology users that have production units and with local technology users that are end users. The degree of engagement in vicarious learning activities with local technology users is positively correlated to the probability of commercializing at least one technology from a particular R&D project. This implies that engaging in vicarious learning activities with local technology users has a positive impact on commercialization of technology.

Hypothesis 3c for Mission 3: Engagement with local users has a negative impact on the NLs' ability to build R&D capabilities for the future needs of the country.

Hypothesis 3c could not be confirmed (the null hypothesis could not be rejected, $p > .05$) for contextual learning. The degree of engagement in contextual learning activities with local technology users is not correlated with statistical significance to the probability of generating at least one publication from a particular project. This implies that contextual learning activities with local technology users have no statistically significant impact on developing a long-term R&D capability of the national laboratories.

Hypothesis 3c has been confirmed (the null hypothesis has been rejected, $p < .001$) for vicarious learning activities with local technology users that have production units and with LTUs that are end users, if performance is measured by the probability of publication. The degree of engagement in vicarious learning activities with local technology users is inversely correlated to the probability of generating at least one publication from a particular project. This implies that engaging in vicarious learning activities with local technology users that are production units and end users has a negative impact on the ability to generate publications. Engaging in vicarious learning activities with local technology users should thus inhibit the national laboratories' ability to develop a long-term R&D capability.

Hypothesis 3c could not be confirmed (the null hypothesis could not be rejected, $p > .05$) for vicarious learning, if performance is measured by versatility of technology. The degree of engagement in vicarious learning activities with local technology users is not correlated with statistical significance to the versatility of the technology that under development in a particular project. This implies that vicarious learning activities with local technology users have no statistically significant impact on developing a long-term R&D capability of the national laboratories.

5.4.4 Engaging with International Sources²⁵

Hypothesis 4a for Mission 1: Engagement with international sources has a positive impact on the satisfaction of LTUs.

Hypothesis 4a could not be confirmed (the null hypothesis could not be rejected, $p > .05$) for contextual learning. The degree of engagement in contextual learning activities with international sources is not correlated with statistical significance to user satisfaction. This implies contextual learning from international sources has no significant impact on user satisfaction.

Hypothesis 4a could not be confirmed (the null hypothesis could not be rejected, $p > .05$) for vicarious learning. The degree of engagement in vicarious learning activities with international sources is not correlated with statistical significance to user satisfaction. This implies vicarious learning from international sources has no significant impact on user satisfaction.

Hypothesis 4b for Mission 2: Engagement with international sources has a positive impact on the NLS' ability to generate revenue for themselves by commercializing technology that they have developed.

Hypothesis 4b could not be confirmed (the null hypothesis could not be rejected, $p > .05$). The degree of engagement in external learning activities of any kind with international

²⁵ Hypotheses 4a, 4b and 4c pertain to external learning with international sources. Hypotheses 4a, 4b and 4c respectively pertain to missions 1, 2 and 3

sources is not correlated with statistical significance to the probability of commercializing at least one technology from a particular project. This implies that external learning activities with international sources have no statistically significant impact on commercialization of technology.

*Hypothesis4c for Mission 3: Engagement with international sources has a **positive** impact on the NLs' ability to build R&D capabilities for the future needs of the country.*

Hypothesis 4c has been confirmed (the null hypothesis has been rejected), for external learning with international sources ($p < .001$ for contextual and $p = .01$ for vicarious). The degree of engagement in external learning activities with international sources is positively correlated to the probability of generating at least one publication from a particular project and to the versatility of the technology under development. This implies that engaging in external learning activities with international sources has a positive impact on the ability to generate publications, regardless of whether these learning activities are contextual or vicarious. In addition engaging in external learning activities, be they contextual or vicarious, increases the versatility of the technology under development. Engaging in external learning activities with international sources should thus enhance the national laboratories' ability to develop a long-term R&D capability.

5.4.5 Relative Impact on Performance

Table 5.11: Impact of Knowledge Inflows on the NLs' Performance

RQ.	Hyp.	Predictors					Output Measurement		p-value	Hypothesis Testing		
		Exo- genous Source	Inflow/ Internal Mech- anism	Q. (App.B)	Variables	Factors	Critical Mission	Q. (App.B)				
RQ-1	1a	ORDU	1.CLAs	Q11,15	IV1,5	FIV8	M1	Q39	>.05	null not rej.		
			2.VLAs	Q19,24	IV9,14	FIV5			>.05	null not rej.		
	1b	ORDU	1.CLAs	Q11,15	IV1,5	FIV8	M2	Q40	>.05	null not rej.		
			2.VLAs	Q19,24	IV9,14	FIV5			0.002	refuted		
	1c	ORDU	1.CLAs	Q11,15	IV1,5	FIV8	M3.1	Q3	>.05	null not rej.		
							M3.3	Q41	.023	confirmed		
			2.VLAs	Q19,24	IV9,14	FIV5	M3.1	Q3	.004	confirmed		
	M3.3	Q41					.023	confirmed				
	2a	LocUniv	3.CLAs	Q12,16	IV2,6	FIV9	M1	Q39	.031	confirmed		
			4.VLAs	Q20,25	IV10,15	FIV3			>.05	null not rej.		
	2b	LocUniv	3.CLAs	Q12,16	IV2,6	FIV9	M2	Q40	>.05	null not rej.		
			4.VLAs	Q20,25	IV10,15	FIV3			>.05	null not rej.		
	2c	LocUniv	3.CLAs	Q12,16	IV2,6	FIV9	M3.1	Q3	>.05	null not rej.		
							M3.3	Q41	>.05	null not rej.		
			4.VLAs	Q20,25	IV10,15	FIV3	M3.1	Q3	.001	confirmed		
	M3.3	Q41					>.05	null not rej.				
	3a	LTUs	5.CLAs	Q14,18	IV4,8	FIV7	M1	Q39	>.001	confirmed		
									6.VLAs	Q22,23	IV12,17	FIV1
				Q27,28	IV13,18	FIV4	>.001	confirmed				
	3b	LTUs	5.CLAs	Q14,18	IV4,8	FIV7	M2	Q40	>.05	null not rej.		
									6.VLAs	Q22,23	IV12,17	FIV1
				Q27,28	IV13,18	FIV4	>.001	confirmed				
	3c	LTUs	5.CLAs	Q14,18	IV4,8	FIV7	M3.1	Q3	>.05	null not rej.		
							M3.3	Q41	>.05	null not rej.		
			6.VLAs	Q22,23	IV12,17	FIV1	M3.1	Q3	.001	confirmed		
								Q27,28	IV13,18	FIV4	.002	confirmed
								Q22,23	IV12,17	FIV1	>.05	null not rej.
		Q27,28	IV13,18	FIV4	>.05	null not rej.						
	4a	InatSrc	7.CLAs	Q13,17	IV3,7	FIV6	M1	Q39	>.05	null not rej.		
			8.VLAs	Q21,26	IV11,16	FIV2			>.05	null not rej.		
4b	InatSrc	7.CLAs	Q13,17	IV3,7	FIV6	M2	Q40	>.05	null not rej.			
		8.VLAs	Q21,26	IV11,16	FIV2			>.05	null not rej.			
4c	InatSrc	7.CLAs	Q13,17	IV3,7	FIV6	M3.1	Q3	>.001	confirmed			
						M3.3	Q41	.039	confirmed			
		8.VLAs	Q21,26	IV11,16	FIV2	M3.1	Q3	.001	confirmed			
M3.3	Q41					.010	confirmed					

Table 5.11 summarizes the results that pertain to research question RQ-1. Initially, this study proposed 12 hypotheses, out of which 8 hypotheses were statistically significant. Also, table 5.11 shows that the results are nuanced and differentiated. Out of 36 results that pertained to RQ-1, 17 were statistically significant. Out of these 14, 13 confirmed the stated hypothesis and one refuted it. The difference between a statistically significant and a statistically insignificant result could depend on the mission and on whether learning was contextual or vicarious.

The relative impact of input factors and moderating factors on performance can be deduced by comparing the correlation coefficients of the statistically significant factors in the various models in appendixes G.1 to G.4. For example, the integrated model for mission 1 (appendix G.1) ranks the relative positive impact of statistically significant factors on user satisfaction as follows:

1. FIV1_LTUsPU_VLAs (Vicarious Learning with LTUs with production units) (B = 0.710)
2. FIV4_LTUsEU_VLAs (Vicarious Learning with LTUs that are end users) (B = 0.591)
3. FIV7_LTUs_CLAs (Contextual Learning about local technology users) (B = 0.513)
4. FMV3_PrExp_Wk_LTUs (Prior work experience at a local technology user) (B = 0.366)

Clearly and not surprisingly, acquiring knowledge from local technology users through vicarious learning, contextual learning and grafting had the biggest impact on user satisfaction. However, the following factors should also not be neglected. They indicate in conjunction with the four dominant factors from above that very local phenomena drive user satisfaction.

5. FMV6_PrExp_Ed_LocUniv (Prior education at a local university) (B = 0.178)
6. FMV5_PrKn_Core (Prior knowledge about the core technology) (B = 0.170)
7. FIV9_LocUniv_CLAs (Contextual learning about a local university) (B = 0.159)
8. FMV1_PILAs (Project-internal learning activities) (B = 0.153)

The integrated model for mission 2 (logistic regression, appendix G.2) ranks the relative positive impact of statistically significant factors on the probability of commercialization as follows:

1. FIV1_LTUsPU_VLAs (Vicarious Learning with LTUs with production units) (B = 1.820)
2. FIV4_LTUsEU_VLAs (Vicarious Learning with LTUs that are end users) (B = 1.072)
3. FMV3_PrExp_Wk_LTUs (Prior work experience at a local technology user) (B = 1.006)

Acquiring knowledge from local technology users through vicarious learning and grafting had the biggest impact on the probability of commercialization. However, the following factors should not be neglected, and two of them even appear in conflict. Vicarious learning with other R&D project groups within the national laboratories had a negative impact on the probability of commercialization, whereas inviting someone from another project group had a positive impact.

4. FIV5_ORDU_VLAs (Vicarious learning with other groups within the labs) (B = -0.700)
5. FMV4_PrExp_Wk_ORDU (Prior work experience at other groups within labs) (B = +0.509)
6. FMV5_PrKn_Core (Prior knowledge about the core technology) (B = +0.415)

The integrated model for mission 3--OV3.1 (logistic regression, appendix G.3) ranks the relative positive impact of statistically significant factors on the probability of generating a publication as follows:

1. FMV2_PrKn_PJ (Prior knowledge of the context of the project) (B = 0.833)
2. FIV6_InatSrc_CLAs (Contextual learning about international sources) (B = 0.802)
3. FIV3_LocUniv_VLAs (Vicarious learning activities with local universities) (B = 0.713)
4. FIV2_InatSrc_VLAs (Vicarious learning activities with international sources) (B = 0.601)
5. FIV5_ORDU_VLAs (Vicarious learning with other groups within labs) (B = 0.572)
6. FMV5_PrKn_Core (Prior knowledge about the core technology) (B = 0.446)
7. FMV8_PrExp_Wk_InatSrc (Prior work experience with international sources) (B = 0.416)

Two factors have a negative impact on the probability of generating a publication.

8. FIV4_LTUsEU_VLAs (Vicarious Learning with LTUs that are end users) (B = -0.588)
9. FIV1_LTUsPU_VLAs (Vicarious Learning with LTUs with production units) (B = -0.637)

The integrated model for mission 3, criterion 3 (OV3.3, multiple regression, appendix G.4) ranks the relative positive impact of statistically significant factors on the versatility of the technology under development as follows:

1. FMV8_PrExp_Wk_InatSrc (Prior work experience with international sources) (B = 0.262)
2. FIV2_InatSrc_VLAs (Vicarious learning activities with international sources) (B = 0.208)
3. FIV5_ORDU_VLAs (Vicarious learning with other groups within labs) (B = 0.185)
4. FIV8_ORDU_CLAs (Contextual learning activities with other groups within labs)(B = 0.184)
5. FIV6_InatSrc_CLAs (Contextual learning about international sources) (B = 0.167)

This ranking implies that the versatility of the technology under development in a project is primarily a function of engaging with international sources and engaging with other R&D project groups within the national laboratories.

The ranking for mission 3 is very different from that of mission 1 and that of mission 2. Knowledge from or about local technology users is the dominant theme of missions 1 and 2, regardless whether it is obtained through contextual learning, vicarious learning or grafting. Mission 3 relies heavily on international sources of knowledge through contextual learning, vicarious learning and grafting. Prior externalized knowledge and prior knowledge about the core technology is also important, as is vicarious learning with other R&D project groups. Vicarious learning with local technology users has a negative impact on publication, and it limits the versatility of the technology under development.

It should also be noted that in missions 1 and 2 vicarious learning has a stronger impact on performance than contextual learning. This is not necessarily true for mission 3. Finally, there is an alignment between vicarious learning and grafting in all missions. In missions 1 and 2, vicarious learning with and grafting people with experience from local technology users both exhibit a positive correlation to performance. In mission 3, vicarious learning with and grafting people with experience from international sources both exhibit a positive correlation to performance.

5.5 INTERACTION EFFECTS

Table 5.12: Regression analysis for Interaction Model (Research Questions 2, 3 & 4; Hypotheses 5, 6 & 7)

RQ.	Hyp.	Predictors					Output Measurement		Hypothesis Testing
		Exo- genous Source	Inflow/ Internal Mech- anism	Q. (App.B)	Variables	Factors	Critical Mission	Q. (App.B)	
RQ-2	5.a	InatSrc	7.CLAs	Q13,17	IV3,7	FIV6	M1	Q39	confirmed
			8.VLAs	Q21,26	IV11,16	FIV2	M2	Q40	confirmed
			9.PrKn	Q7-Q10,Q38	MV2,14,1	FMV2,5	M3.1, 3.3	Q3,Q41	confirmed
	5.b	LocUniv	3.CLAs	Q12,16	IV2,6	FIV9	M1	Q39	confirmed
			4.VLAs	Q20,25	IV10,15	FIV3	M2	Q40	confirmed
			9.PrKn	Q7-Q10,Q38	MV2,14,1	FMV2,5	M3.1, 3.3	Q3,Q41	confirmed
	5.c	LTUs	3.CLAs	Q12,16	IV2,6	FIV9	M1	Q39	null not rej.
			4.VLAs	Q20,25	IV10,15	FIV3	M2	Q40	confirmed
			9.PrKn	Q7-Q10,Q38	MV2,14,1	FMV2,5	M3.1, 3.3	Q3,Q41	confirmed
	5.d	ORDU	3.CLAs	Q12,16	IV2,6	FIV9	M1	Q39	confirmed
			4.VLAs	Q20,25	IV10,15	FIV3	M2	Q40	confirmed
			9.PrKn	Q7-Q10,Q38	MV2,14,1	FMV2,5	M3.1, 3.3	Q3,Q41	confirmed
RQ-3	6.a	ORDU	1.CLAs	Q11,15	IV1,5	FIV8	M1	Q39	confirmed
			2.VLAs	Q19,24	IV9,14	FIV5	M2	Q40	null not rej.
			10.PrExp	Q33-Q37	IV12,13,10,9,11	FMV3,4,6,7,8	M3.1, 3.3	Q3,Q41	confirmed
	6.b	LocUniv	3.CLAs	Q12,16	IV2,6	FIV9	M1	Q39	confirmed
			4.VLAs	Q20,25	IV10,15	FIV3	M2	Q40	confirmed
			10.PrExp	Q33-Q37	IV12,13,10,9,11	FMV3,4,6,7,8	M3.1, 3.3	Q3,Q41	confirmed
	6.c	LTUs	5.CLAs	Q14,18	IV4,8	FIV7	M1	Q39	confirmed
			6.VLAs	Q22,23,27,28	IV12,17,13,18	FIV1,4	M2	Q40	confirmed
			10.PrExp	Q33-Q37	IV12,13,10,9,11	FMV3,4,6,7,8	M3.1, 3.3	Q3,Q41	confirmed
	6.d	InatSrc	7.CLAs	Q13,17	IV3,7	FIV6	M1	Q39	null not rej.
			8.VLAs	Q21,26	IV11,16	FIV2	M2	Q40	null not rej.
			10.PrExp	Q33-Q37	IV12,13,10,9,11	FMV3,4,6,7,8	M3.1, 3.3	Q3,Q41	confirmed
RQ-4	7.a	InatSrc	7.CLAs	Q13,17	IV3,7	FIV6	M1	Q39	null not rej.
			8.VLAs	Q21,26	IV11,16	FIV2	M2	Q40	confirmed
			11.PILAs	Q29-Q32	MV5,6,7,8	FMV1	M3.1, 3.3	Q3,Q41	confirmed
	7.b	LocUniv	3.CLAs	Q12,16	IV2,6	FIV9	M1	Q39	null not rej.
			4.VLAs	Q 20,25	IV10,15	FIV3	M2	Q40	null not rej.
			11.PILAs	Q29-Q32	MV5,6,7,8	FMV1	M3.1, 3.3	Q3,Q41	confirmed
	7.c	LTUs	5.CLAs	Q14,18	IV4,8	FIV7	M1	Q39	confirmed
			6.VLAs	Q22,23,27,28	IV12,17,13,18	FIV1,4	M2	Q40	confirmed
			11.PILAs	Q29-Q32	MV5,6,7,8	FMV1	M3.1, 3.3	Q3,Q41	confirmed
	7.d	ORDU	1.CLAs	Q11,15	IV1,5	FIV8	M1	Q39	null not rej.
			2.VLAs	Q19,24	IV9,14	FIV5	M2	Q40	null not rej.
			11.PILAs	Q29-Q32	MV5,6,7,8	FMV1	M3.1, 3.3	Q3,Q41	null not rej.

Table 5.12 summarizes the results that concern to interaction effects. It shows that 10 out of 12 hypotheses that relate to interaction effects have been confirmed. All of the original research questions pertaining to interaction effects have been answered at least in part.

The interaction model generated a total of 192 interactions between input factors pertaining to knowledge inflow (FIV1 through FIV9) and moderating factors pertaining to internal knowledge (FMV1 through FMV8).²⁶ Every interaction is associated with a unique combination of output variable, source of external knowledge, type of knowledge inflow (either contextual or vicarious) and type of internal knowledge. The interaction matrices in table 5.13 depict the hypotheses that were confirmed (the null hypothesis was rejected) by one or more of these combinations at the level of $p < 0.05$.²⁷ Yet, the interaction matrices as a whole appear quite sparse because no hypothesis pertaining to interactions could be confirmed under all sets of circumstances. Only 39 out of 192 possible interactions were found to be statistically significant at the level of $p < 0.05$. An additional seven interactions were considered potentially significant by SPSS (see non-shaded interactions in interaction appendix G.7).

²⁶ FIV8, FMV6 and FMV7 were excluded from the interaction model because the integrated model indicated that they have less of impact on the performance of the national laboratories three critical missions than the other factors do. FIV8 pertains to contextual learning from other R&D project groups within the national laboratories; it only impacts versatility of technology. FMV6 is associated with prior education at local universities; it only impacts user satisfaction. FMV7 is associated with prior education at foreign universities; it has no significant impact on any output variable.

²⁷ The null hypotheses could not be rejected under all sets of circumstances in only two cases: hypothesis 6d and hypothesis 7d. Even here there are caveats. SPSS identified the interaction between VLAs with ORDUs and PILAs as a potentially significant factor for user satisfaction. However, the level significance was at $p = 0.062$. According to appendix G.7, many interactions had a statistically significant impact on OV3.2, the probability of generating a patent. However, it has been determined in section 5.3 that knowledge inflows and internal knowledge were not major drivers of the propensity to generate a patent. The results for OV3.2 have consequently been excluded from this dissertation.

Table 5.13: Interaction Matrices for Missions 1, 2 and 3

Mission 1 (OV1): User Satisfaction

	(+) FIV1	(-) FIV2	FIV3	(+) FIV4	FIV5	FIV6	(+) FIV7	FIV8	(+) FIV9
(+) FMV1							H.7c		
FMV2					H.5d				
(+) FMV3	H.6c			H.6c					H.6b
FMV4	H.6c				H.6a		H.6c		H.6b
FMV5		H.5a	H.5b						
FMV6	Not included in interaction model								
FMV7	Not included in interaction model								
FMV8				H.6c					

Mission 2 (OV2): Probability of Commercialization

	(+) FIV1	FIV2	FIV3	(+) FIV4	(-) FIV5	FIV6	(+) FIV7	FIV8	(+) FIV9
FMV1		H.7a					H.7c		
FMV2					H.5d				H.5b
(+) FMV3							H.6c		H.6b
FMV4									
(+) FMV5	H.5c	H.5a		H.5c	H.5d	H.5a	H.5c		
FMV6	Not included in interaction model								
FMV7	Not included in interaction model								
FMV8									

Mission 3 (OV3.1): Probability of Publication

	(-) FIV1	(+) FIV2	(+) FIV3	(-) FIV4	(+) FIV5	(+) FIV6	FIV7	FIV8	FIV9
FMV1		H.7a							H.7b
(+) FMV2									H.5b
FMV3									
(-) FMV4					H.6a		H.6c		
FMV5		H.5a							
FMV6	Not included in interaction model								
FMV7	Not included in interaction model								
(+) FMV8				H.6b					

Mission 3 (OV3.3): Versatility of Technology

	(-) FIV1	(+) FIV2	FIV3	FIV4	(+) FIV5	(+) FIV6	FIV7	FIV8	FIV9
(+) FMV1				H.7c		H.7a	H.7c		H.7b
FMV2					H.5d		H.5c		
FMV3									
(-) FMV4									H.6b
FMV5									
FMV6	Not included in interaction model								
FMV7	Not included in interaction model								
(+) FMV8							H.6c		

(+)	Factor that is positively correlated to output
(-)	Factor that is negatively correlated to output
H.xx	Complementary interaction
H.xx	Interaction where FMV has a negative impact
H.xx	Interaction where FIV has a negative impact
H.xx	Substitutive interaction
	Not included in interaction model

Table 5.13 indicates which input factors (FIVs) and which moderating factors (FMVs) in the interaction model have a statistically significant impact on performance by themselves and which do not. Factors with (+) have a positive impact; factors with (-) have a negative impact on performance; factors with no shading do not have a statistically significant impact on performance. As has been shown by the integrated model from section 5.3.2 and the correlation matrix from section 5.2, these factors do not necessarily align from mission to mission.

5.5.1 Types of Interactions

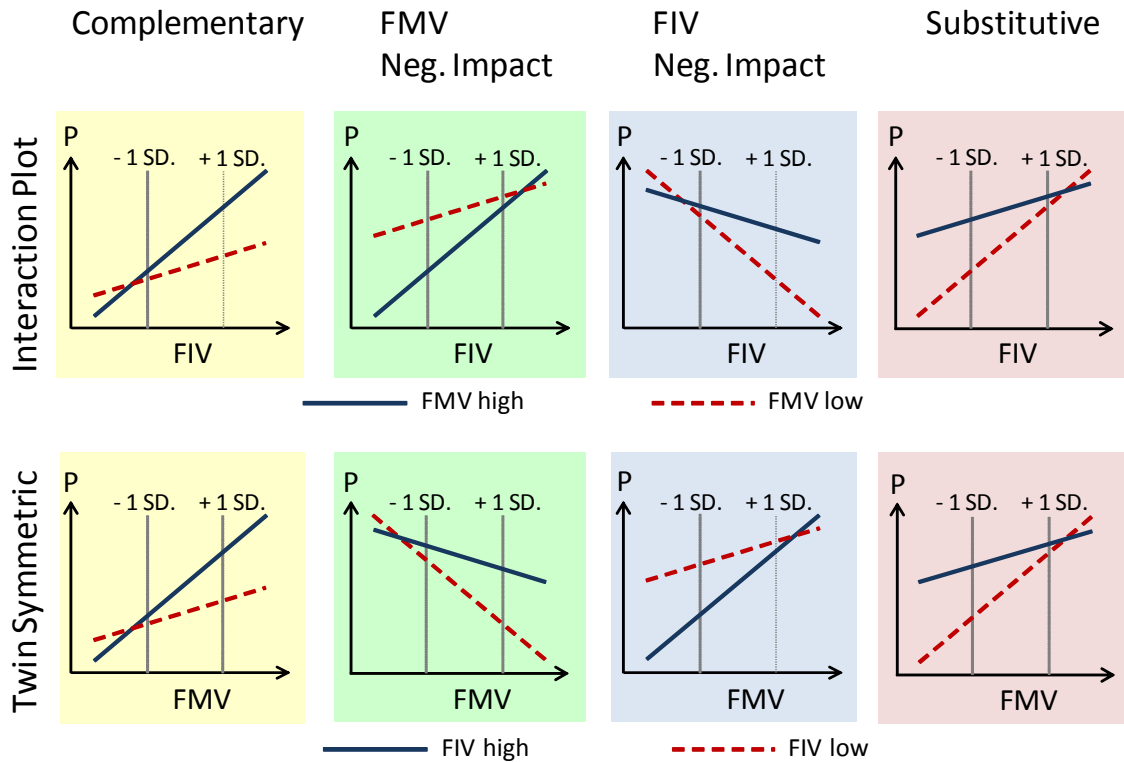


Figure 5.1: Types of interactions that were observed in this study

Figure 5.1 displays the four types of interaction that were observed in this study, as well as their symmetric twins. Issues associated with each type of interaction are discussed in this section. I also give an example of each kind of interaction.

5.5.1.1 Complementary Interactions

Complementary interactions have a positive impact on performance. Three types of complementary interactions were observed. In the first, neither the input factor nor the moderating factor has a negative impact on performance (*i.e.*, the input factor by itself and the moderating factor by itself had a positive or a statistically insignificant impact on

performance). This case is shown in the first column of figure 5.1 in the second type of interaction; the moderating factor had a negative impact on performance, whereas the input factor did not. This case is shown in the second column of figure 5.1. In the third type of interaction, the input factor had a negative impact on performance, whereas the moderating factor did not. This case is shown in the third column of figure 5.1.

- **5.5.1.1.1 Neither the Input Factor nor the Moderating Factor has a Negative Impact on Performance.**

Let us first consider the case when neither the input factor by itself nor the moderating factor by itself had a negative impact on performance. In that case, over most of the domain of the input factor, performance was higher when the moderating factor was high, and performance increased more rapidly as a function of the input factor when the moderating factor was high. However, for a small fraction of the population at the lower end of the domain of the input factor, the situation was different. Performance was higher when the moderating factor was low, even though performance increased more rapidly as a function of the input factor when the moderating factor was high.

The symmetric twin of the interaction plot told a similar story. Over most of the domain of the moderating factor, performance was higher when the input factor was high, and performance increased more rapidly as a function of the moderating factor when the input factor was high. However, for a small fraction of the population at the lower end of the domain of the moderating factor, the situation was different. Performance was higher when the input factor was low, even though performance increased more rapidly as a function of the moderating factor when the input factor was high.

The normative implications for the managers in the national laboratories are straightforward. They need to increase the input factor and the moderating factor as much as possible. This is illustrated by the interaction between contextual learning about local universities (FIV9) and hiring people with prior work experience at local technology users (FMV3) into the R&D project group. This interaction has a positive impact on the probability of commercializing technology. The analysis of this case is given below.

For a specific set of circumstances, hypothesis 6b was confirmed (the null hypothesis was rejected) for Mission 2. Having at least one employee with prior work experience at a local technology user in the project team for the duration of the project enhances the project group's capacity to absorb knowledge that flows into the project group from local universities through contextual learning activities. Contextual learning from local universities has a positive impact on the probability of commercializing technology by itself. Having an employee with work experience at a local technology user in the project group enhances the positive impact of contextual learning from local universities.

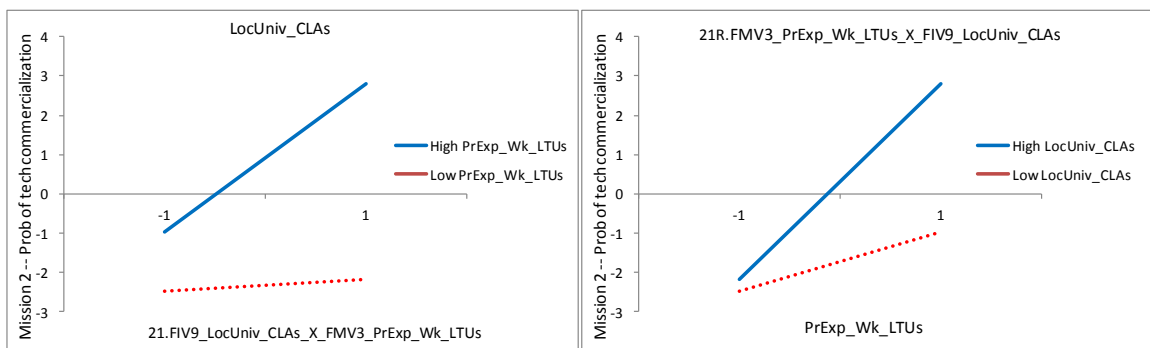


Figure 5.2: The impact of the interaction between contextual learning about local universities and having at least one team member with prior work experience at a local technology user on the probability of commercialization (on the left, and the symmetric interaction plot on the right).

The interaction plots in figure 5.2 show that, over most of the domain of contextual learning from local universities, the probability of commercialization is higher and rises more rapidly as a function contextual learning when the number of project group members with prior work experience at local technology users is high, rather than when the number of project group members with work experience is low. The symmetric interaction plot in figure 5.2 suggests that, over most of the domain of the number of project group members with prior work experience at local technology users, the probability of commercialization is higher and rises more rapidly when the degree of contextual learning from local universities national laboratories is high, rather than when the degree of contextual learning from local universities national laboratories is low. This suggests that the national laboratories need to increase contextual learning activities with local universities and to hire people with work experience at local technology users into R&D project groups, if they want to increase the odds of commercialization of technology.

- **5.5.1.1.2 The Moderating Factor has a Negative Impact on Performance, but the Input Factor Does Not.**

Next, let us consider the case when the impact on performance of the moderating factor was negative but that of the input factor was not. In that case, over most of the domain of the input factor, performance was higher when the moderating factor was low, and performance increased more rapidly as a function of the input factor when the moderating factor was high. However, for a small fraction of the population at the upper end of the domain of the input factor, the situation was different. Performance was higher when the

moderating factor was high, and performance increased more rapidly as a function of the input factor when the moderating factor was high.

The symmetric twin of the interaction plot told a very different story. Performance decreases as the moderating factor increases. Over most of the domain of the moderating factor, performance was higher when the input factor was high, but performance decreased more rapidly as a function of the moderating factor when the input factor was low. However, for a small fraction of the population at the lower end of the domain of the moderating factor, the situation was different. Performance was higher when the input factor was low, even though performance decreased more rapidly as a function of the moderating factor when the input factor was low.

The normative implications of this scenario are slightly different from those of the case described above. The managers of the national laboratories need to increase the input factor as much as possible, but keep the moderating factor low. This situation is illustrated by the interaction between vicarious learning with other R&D project groups in the national laboratories (FIV5) and inviting people with prior work experience at other R&D project groups (FMV3) into the R&D project group. The analysis of this case is given below.

Hypothesis 6a was confirmed (the null hypothesis was rejected) for vicarious learning with another R&D project group within the national laboratories for mission 3. Vicarious learning with other R&D project groups within the national laboratories has a positive impact on the probability of generating a publication from a particular project. However, having employees with work experience in another R&D project group within the

national laboratories in the project group for the duration of the project has a direct negative impact on the probability of generating publications from the project; it does not impede knowledge inflows from ORDUs. Therefore, this phenomenon is not a substitution effect.

The pair of interaction plots in figure 5.3 shows that, for most of the domain of vicarious learning with other R&D project groups, the probability of publications is higher when the project group contains few or no employees with prior work experience at another R&D project group within the national laboratories. However, the probability of publication increases at a more rapid rate when the project group contains more employees with prior work experience at another project group. The probability of publication is higher when the number of team members with work experience at other R&D project groups is high, only if the degree of vicarious learning with other R&D project groups is very high. The symmetric interaction plot suggests that, if the degree of vicarious learning with the other R&D project group is low, then the probability of generating a publication decreases sharply as the number of group members with prior work experience at another R&D project group increases. The probability of generating a publication is not particularly sensitive to the number of group members with prior work experience at another project group, if the degree of vicarious learning with other project groups is high.

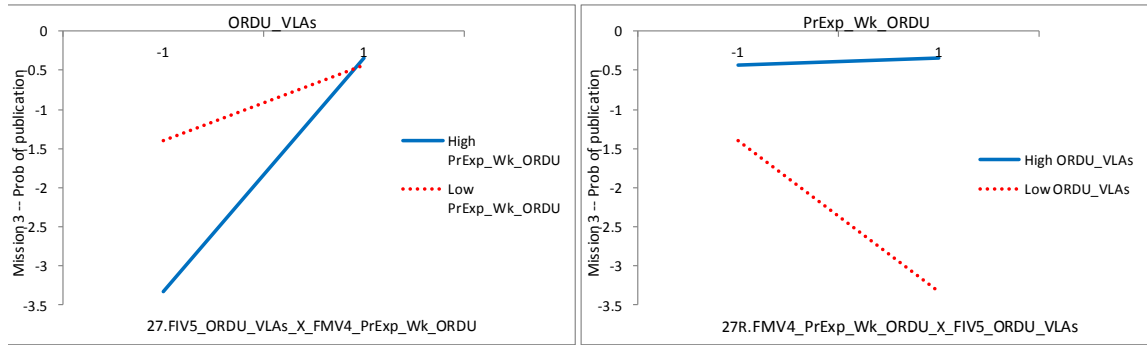


Figure 5.3: The impact of the interaction between vicarious learning with other R&D project groups within the national laboratories and having at least one team member with prior work experience in another R&D project group within the national laboratories on the probability of generating at least one publication from a project (on the left, and the symmetric interaction plot on the right).

- **5.5.1.1.3 The Input Factor has a Negative Impact on Performance, but the Moderating Factor Does Not.**

Finally, let us consider the case when the input factor has a negative impact on performance, whereas the moderating factor did not. In that case, performance was inversely correlated to the input factor. Over most of the domain of the input factor, performance was higher when the moderating factor was high, but performance decreased more rapidly as a function of the input factor when the moderating factor was low. However, for a small fraction of the population at the lower end of the domain of the input factor, the situation was different. Performance was higher when the moderating factor was low, and performance decreased more rapidly as a function of the input factor when the moderating factor was low.

The symmetric twin of the interaction plot told a very different story. Performance increases as the moderating factor increases. Over most of the domain of the moderating factor, performance was higher when the moderating factor was low, but performance increased more rapidly as a function of the moderating factor when the input factor was

high. However, for a small fraction of the population at the upper end of the domain of the moderating factor, the situation was different. Performance was higher when the input factor was high, and performance increased more rapidly as a function of the moderating factor when the input factor was high.

The normative implications of this scenario are slightly different from those of the case described above. The managers of the national laboratories need to keep the input factor low, but keep the moderating factor high. This situation is illustrated by the interaction between vicarious learning with other R&D project groups in the national laboratories (FIV5) and having prior knowledge about the core technology within the project group before the project begins (FMV5). The analysis of this case is given below.

Hypothesis 5d was confirmed (the null hypothesis was rejected) for Mission 2. Having prior knowledge about the core technology within the project group at the outset of the project increases the probability of commercializing technology. It also enhances the project group's capacity to absorb knowledge that flows into the project group from other R&D project groups within the national laboratories through vicarious learning activities. However, vicarious learning with other R&D project groups (ORDUs) has a directly negative impact on the probability that a technology that is developed in a particular project group will be commercialized. Thus, prior knowledge about the core technology enhances the negative impact of vicarious learning with other R&D project groups. It is not a substitute for vicarious learning with ORDUs.

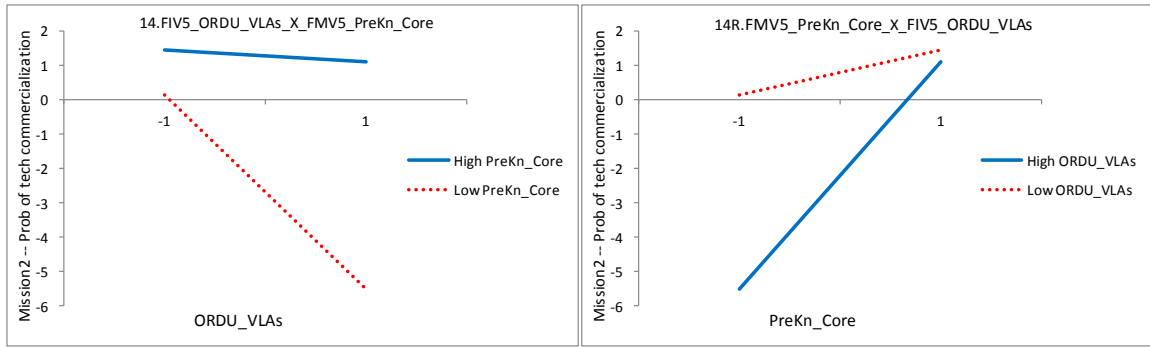


Figure 5.4: The impact of the interaction between vicarious learning with other R&D project groups and prior knowledge of the core technology on the probability of commercializing technology (on the left, and the symmetric interaction plot on the right).

The interaction plots in figure 5.4 illustrate that performance is higher over most of the domain of vicarious learning with ORDUs when prior knowledge about the core technology is high, rather than when it is low. When prior knowledge about the core technology is low, then the probability of commercialization decreases at a very rapid rate as the degree of vicarious learning with ORDUs increases. This rate of decrease is significantly less when prior knowledge about the core technology is high. When vicarious learning with ORDUs is very low, then the probability of commercialization is actually higher if knowledge of about the core technology is high.

The symmetric plot suggests that the probability of commercialization is directly proportional to the degree of prior knowledge about the core technology. The probability of commercialization is higher over most of the domain of prior knowledge about the core technology when vicarious learning with LTUs is low. However, rate of increase in the odds of commercialization is higher when the degree of vicarious learning with ORDUs is high. When knowledge of about the core technology is very high, then the odds of commercialization are actually higher if vicarious learning with ORDUs is high.

5.5.1.2 Substitutive Interactions

Substitutive interactions have a negative impact on performance. The input factors and the moderating factors of the substitutive interactions that were observed in this research all had a positive impact on performance or a statistically insignificant impact on performance. This case is shown in the fourth column of figure 5.1.

No substitutive interaction that was observed had an impact factor or a moderating factor with a negative impact on performance. Over most of the domain of the input factor, performance was higher when the moderating factor was high, but performance increased more rapidly as a function of the input factor when the moderating factor was low. However, for a small fraction of the population at the upper end of the domain of the input factor, the situation was different. Performance was higher when the moderating factor was low, and performance increased more rapidly as a function of the input factor when the moderating factor was low.

The symmetric twin of the interaction plot told a similar story. Over most of the domain of the moderating factor, performance was higher when the input factor was high, but performance increased more rapidly as a function of the moderating factor when the input factor was low. However, for a small fraction of the population at the upper end of the domain of the moderating factor, the situation was different. Performance was higher when the input factor was low, and performance increased more rapidly as a function of the moderating factor when the input factor was low.

In the case of substitutive interactions, internal knowledge diminishes the project group's capacity to absorb external knowledge because the source of internal knowledge acts as a substitute for the knowledge inflow. However, a reduced absorptive capacity can also be attributed to other causes. For example, if a project group suffers from the Not-Invented-Here Syndrome (NIH) (R. Katz & Allen, 1982), then it is not likely to be open to knowledge from exogenous sources. In that case, the internal sources of knowledge would not be a substitute for knowledge inflows; instead, they would just be a barrier to knowledge inflows. This situation is illustrated by the interaction between external with local technology users (FIV1, FIV4, FIV7) and having prior knowledge about the core technology within the project group before the project begins (FMV5). The analysis of this case is given below.

Hypothesis 5c was confirmed (the null hypothesis was rejected) for mission 2. External learning with local technology users has a positive effect on the probability of commercializing technology. Having prior knowledge about the core technology in the project group also has a positive impact on the probability of commercialization. Yet the interaction between these two factors reduces the probability of commercialization. This suggests that having prior knowledge about the core technology in the project group at the outset of the project diminishes the project group's capacity to absorb knowledge that flows into the project group from local technology users through external learning activities, be they vicarious or contextual. It also does not matter whether the local technology users are end users or whether they have production units. Thus, having prior knowledge about the core technology in the project group may act as a substitute for engaging in external learning with local technology users. Alternatively, having prior

knowledge about the core technology in the project group may be a source of NIH. Only an investigation into the specific situation will tell.

The interaction plots in figures 5.5 through 5.7 show that the probability of commercializing a technology is higher over most of the external learning domains that pertain to local technology users when prior knowledge of about the core technology is high. However, the probability of commercialization is increases more rapidly as a function of external learning from local technology users when prior knowledge about the core technology is low. At the very upper end of the external learning domain the probability of commercialization is actually higher when prior knowledge about the core technology is low. The symmetric plot suggests that the probability of commercializing a technology is higher over most of the domain knowledge about the core technology when external learning activities with is high. However, the probability of commercialization increases more rapidly as a function of prior knowledge about the core technology when external learning with local technology users is low. At the very upper end of the prior knowledge domain, the probability of commercialization is actually higher when the degree of external learning with local technology users is low.

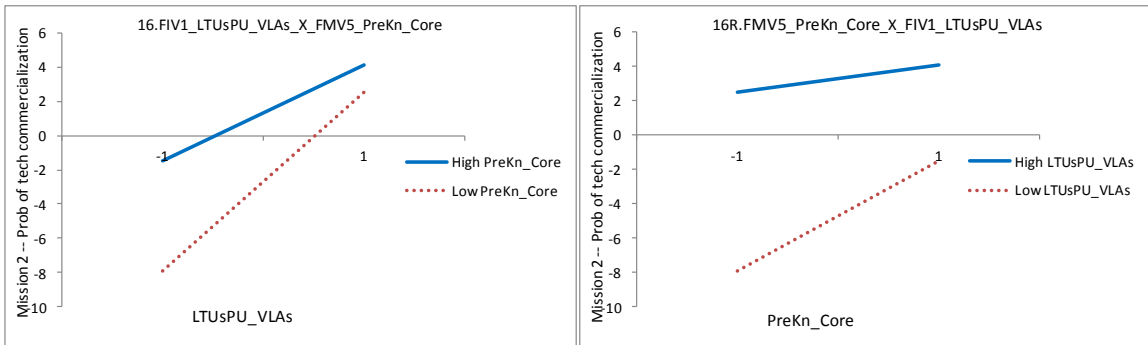


Figure 5.5: The impact of the interaction between vicarious learning with local technology users that have production units and prior knowledge of the core technology on the probability of commercializing technology (on the left, and the symmetric interaction plot on the right).

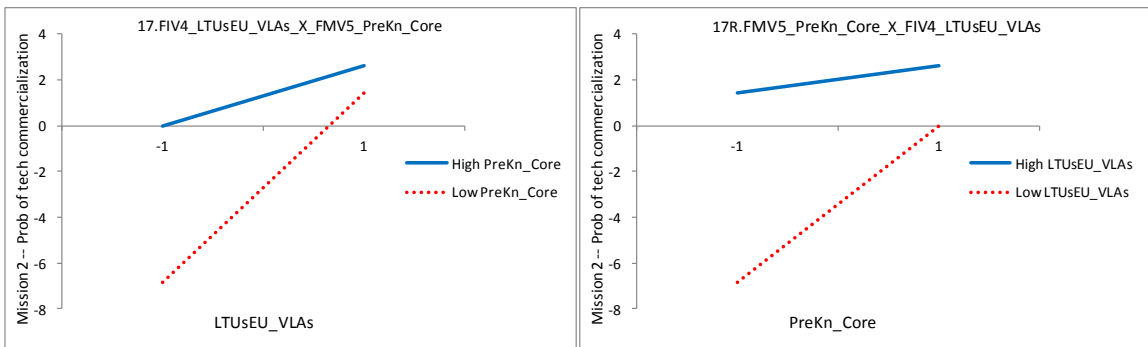


Figure 5.6: The impact of the interaction between vicarious learning with local technology users that are end users and prior knowledge of the core technology on the probability of commercializing technology (on the left, and the symmetric interaction plot on the right).

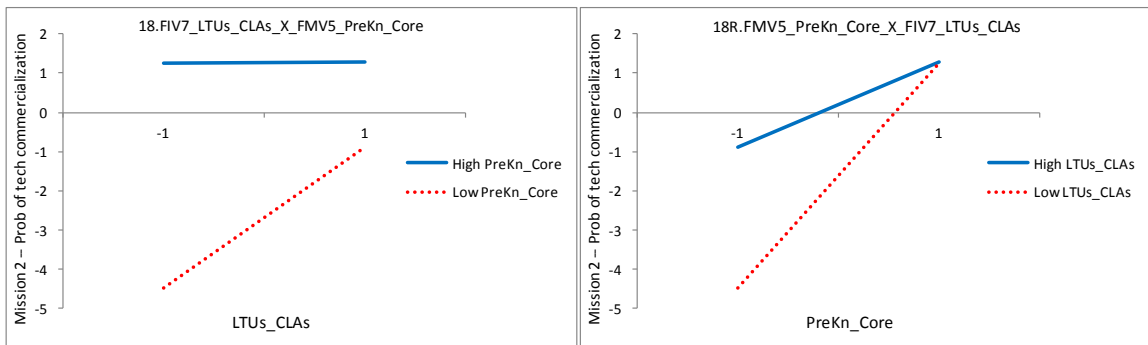


Figure 5.7: The impact of the interaction between contextual learning with local technology users and prior knowledge of the core technology on the probability of commercializing technology (on the left, and the symmetric interaction plot on the right).

5.5.2 Ranking Interaction Effects

Table 5.14: Ranking Interaction Effects

Mission 1 (OV1): User Satisfaction

Interaction:	B	S.E.	Beta	t	Sig.	Interaction Type
1. FIV9_LocUniv_CLAs_X_FMV4_PrExp_Wk_ORDU	.227	.075	.136	3.023	.003	Complementary
2. FIV3_LocUniv_VLAs_X_FMV5_PreKn_Core	.202	.068	.133	2.979	.003	Complementary
3. FIV5_ORDU_VLAs_X_FMV2_PreKn_PJ	.190	.068	.124	2.795	.006	Complementary
4. FIV2_InatSrc_VLAs_X_FMV5_PreKn_Core	.189	.061	.140	3.072	.002	Input Factor Neg. Impact
5. FIV9_LocUniv_CLAs_X_FMV3_PrExp_Wk_LTUs	.179	.063	.131	2.852	.005	Complementary
6. FIV5_ORDU_VLAs_X_FMV4_PrExp_Wk_ORDU	-.234	.068	-.157	-3.441	.001	Substitutive
7. FIV1_LTUsPU_VLAs_X_FMV3_PrExp_Wk_LTUs	-.164	.067	-.108	-2.440	.016	Substitutive
8. FIV7_LTUs_CLAs_X_FMV4_PrExp_Wk_ORDU	-.158	.065	-.106	-2.437	.016	Substitutive
9. FIV4_LTUsEU_VLAs_X_FMV3_PrExp_Wk_LTUs	-.155	.067	-.108	-2.312	.022	Substitutive
10. FIV1_LTUsPU_VLAs_X_FMV4_PrExp_Wk_ORDU	-.151	.067	-.101	-2.268	.025	Substitutive
11. FIV7_LTUs_CLAs_X_FMV1_PILAs	-.149	.065	-.104	-2.292	.023	Substitutive
12. FIV4_LTUsEU_VLAs_X_FMV8_PrExp_Wk_InatSrc	-.144	.065	-.097	-2.207	.029	Substitutive

Mission 2 (OV2): Probability of Commercialization

Interaction:	B	S.E.	Wald	Exp(B)	Sig.	Interaction Type
13. FIV7_LTUs_CLAs_X_FMV3_PrExp_Wk_LTUs	1.426	.378	14.220	4.160	.000	Complementary
14. FIV5_ORDU_VLAs_X_FMV5_PreKn_Core	1.332	.500	7.088	3.789	.008	Input Factor Neg. Impact
15. FIV6_InatSrc_CLAs_X_FMV5_PreKn_Core	1.117	.407	7.522	3.054	.006	Complementary
16. FIV5_ORDU_VLAs_X_FMV2_PreKn_PJ	.871	.368	5.609	2.388	.018	Input Factor Neg. Impact
17. FIV9_LocUniv_CLAs_X_FMV3_PrExp_Wk_LTUs	.870	.271	10.336	2.386	.001	Complementary
18. FIV9_LocUniv_CLAs_X_FMV2_PreKn_PJ	.674	.320	4.423	1.961	.035	Complementary
19. FIV4_LTUsEU_VLAs_X_FMV5_PreKn_Core	-1.41	.569	6.136	.244	.013	Substitutive
20. FIV1_LTUsPU_VLAs_X_FMV5_PreKn_Core	-1.20	.467	6.598	.301	.010	Substitutive
21. FIV7_LTUs_CLAs_X_FMV5_PreKn_Core	-.895	.408	4.812	.409	.028	Substitutive
22. FIV7_LTUs_CLAs_X_FMV1_PILAs	-.842	.375	5.043	.431	.025	Substitutive
23. FIV2_InatSrc_VLAs_X_FMV5_PreKn_Core	-.833	.370	5.061	.435	.024	Substitutive
24. FIV2_InatSrc_VLAs_X_FMV1_PILAs	-.750	.322	5.408	.472	.020	Substitutive

Mission 3 (OV3.1): Probability of Publication

Interaction:	B	S.E.	Wald	Exp(B)	Sig.	Interaction Type
25. FIV7_LTUs_CLAs_X_FMV4_PrExp_Wk_ORDU	.714	.262	7.406	2.043	.006	Mod. Fact. Neg. Impact
26. FIV2_InatSrc_VLAs_X_FMV5_PreKn_Core	.587	.264	4.941	1.799	.026	Complementary
27. FIV5_ORDU_VLAs_X_FMV4_PrExp_Wk_ORDU	.505	.248	4.156	1.657	.041	Mod. Fact. Neg. Impact
28. FIV9_LocUniv_CLAs_X_FMV2_PreKn_PJ	-.736	.281	6.852	.479	.009	Substitutive
29. FIV9_LocUniv_CLAs_X_FMV1_PILAs	-.629	.272	5.334	.533	.021	Substitutive
30. FIV3_LocUniv_VLAs_X_FMV8_PrExp_Wk_InatSrc	-.586	.274	4.581	.557	.032	Substitutive
31. FIV2_InatSrc_VLAs_X_FMV1_PILAs	-.571	.249	5.254	.565	.022	Substitutive

Mission 3 (OV3.3): Versatility of Technology

Interaction:	B	S.E.	Beta	t	Sig.	Interaction Type
32. FIV4_LTUsEU_VLAs_X_FMV1_PILAs	.200	.080	.162	2.503	.013	Complementary
33. FIV7_LTUs_CLAs_X_FMV1_PILAs	.180	.079	.153	2.285	.023	Complementary
34. FIV9_LocUniv_CLAs_X_FMV4_PrExp_Wk_ORDU	.178	.087	.129	2.041	.043	Mod. Fact. Neg. Impact
35. FIV5_ORDU_VLAs_X_FMV2_PreKn_PJ	.172	.081	.141	2.138	.034	Complementary
36. FIV7_LTUs_CLAs_X_FMV2_PreKn_PJ	-.234	.081	-.184	-2.895	.004	Substitutive
37. FIV6_InatSrc_CLAs_X_FMV1_PILAs	-.212	.076	-.174	-2.771	.006	Substitutive
38. FIV7_LTUs_CLAs_X_FMV8_PrExp_Wk_InatSrc	-.191	.081	-.149	-2.358	.019	Substitutive
39. FIV9_LocUniv_CLAs_X_FMV1_PILAs	-.167	.077	-.139	-2.172	.031	Substitutive

Table 5.14 ranks the interactions that were statistically significant at the level of $p < 0.05$ by magnitude of correlation coefficient. This ranking has been performed for OV.1, OV.2, OV3.1 and OV3.3; thus all three critical missions of the national laboratories are covered. Table 5.14 also identifies complementary interactions for which the input factor or the moderating factor has negative impact on performance.

The ranking in table 5.14 has resulted in the following observations:

- When it comes to user satisfaction, all statistically significant interactions involving local technology users are substitutive.
- When it comes to user satisfaction, the strongest complementary interaction is between contextual learning about local universities and grafting someone with prior work experience at another R&D project group within the national laboratories into the project group.
- When it comes to the probability of commercialization, the interactions between the various knowledge inflows from local technology users and prior knowledge about the core technology tend to be substitutive. So is the interaction between the contextual learning about local technology users and project-internal learning activities.
- When it comes to the probability of commercialization, the strongest complementary interaction is between contextual learning about local technology users and grafting someone with prior work experience at a local technology user into the project group.
- When it comes to the probability of publication, all interactions involving local universities are substitutive.
- When it comes to versatility of technology, the two strongest complementary interactions are between knowledge inflows from local technology users and project-internal learning activities. The strongest substitutive interaction is

between contextual learning about local technology users and externalized prior knowledge about subject matter that pertains to the project.

- All but one of the interactions for which either the input factor or the moderating factor has a negative impact on performance involve other R&D project groups within the national laboratories.
 - All interactions for which the moderating factor has a negative impact on performance are related to grafting employees with prior work experience at other project groups within the national laboratories into the project group. (This observation is an artifact of the interaction model. The integrated model does not yield statistically significant evidence that grafting people with prior experience at other R&D units has a negative impact on performance.)
 - Two out of three interactions for which the input factor has a negative impact on performance are related to external learning with other project groups within the national laboratories. Both of these interactions impact the probability of commercialization.
 - Two out of three interactions for which the input factor has a negative impact on performance are related to knowledge inflows from other project groups within the national laboratories.
 - Knowledge inflow from international sources by itself has a statistically significant negative impact on user satisfaction in the interaction model, but not in the integrated model.

6. INTERPRETATION AND CONCLUSIONS

In this chapter, I use the qualitative data that was gathered in the interviews with project managers and project evaluators to interpret the quantitative data from chapter 5. This approach leads to a series of conclusions, which are presented in this chapter. In some instances, the conclusions yield suggestions for further research, which are denoted in the form of specific propositions.

The remainder of this chapter is organized thematically. In section 6.1, I draw conclusions that are specific to NSTDA, the national laboratories of Thailand. In section 6.2, I present the overarching conclusion of this dissertation—a framework for knowledge flows for the part of the national innovation system that pertains to the national laboratories. In section 6.3, I conclude that absorption of knowledge is selective—it depends on the source of external knowledge, the source of internal knowledge, the interaction between those sources, the type of knowledge inflow and the mission to which it is applied. I argue that knowledge flows, as they pertain to the national laboratories, can be organized into knowledge subsystems of the national innovation systems, which can be managed at a relatively low level within the national laboratories. In section 6.4, I present the knowledge subsystems that are associated with each of the output variables of my research, and I draw conclusions that are specific to each of the three primary missions of the national laboratories. Section 6.5 discusses the alignment of the mission-specific criteria and their linkage to organizational ambidexterity. Finally, in section 6.6, I present conclusions about the knowledge

subsystems of the national laboratories system that pertain to specific sources of knowledge, and I discuss the relative importance of external and internal sources of knowledge.

6.1 CONCLUSIONS ABOUT NSTDA

The analysis of the descriptive statistics in section 5.1 has yielded a series of statistically significant findings that concern NSTDA.²⁸ Interview with project managers have enabled me to interpret these findings, which have led to the conclusions that are presented in this section.

Conclusion 6.1-1: Contextual learning activities with international sources are more prevalent within NSTDA than contextual learning activities with other R&D project groups, local universities and local technology users.

Interviews with project managers provide the following explanation for conclusion 6.1-1. Before the beginning of an R&D project, the managers need to set up the project's goal and commit to specific deliverables. They subsequently generate research plans that allow them to match the tasks to be completed with the knowledge and skills that their team members possess. If the internal knowledge within individuals or the project groups is not sufficient for the team to complete the new project, then the team conducts a review of relevant technical literature (a form of contextual learning), in order to gain

²⁸ The statistical significance was determined by a t-test of select pairs of variables within the descriptive statistics.

new ideas for the project. For example, the project group can rely on international online research databases as a source of explicit knowledge that can stimulate new ideas.

Conclusion 6.1-2: Grafting people with prior relevant experience in education is more prevalent than grafting people with prior relevant work experience at international sources, local technology users or other R&D units within the national laboratories.

The interviews with the project managers suggest that, typically, most of their researchers graduate from universities both local and abroad. They also tend to have gained research experience in specific areas of technology from their research projects while studying at universities. The research skills from their education are considered a fundamental source of knowledge for their research projects.

Grafting people with prior relevant work experience into a project group tends to be less common than education abroad. International work experience of project members tends to come from collaborative projects with international institutes that occur on occasion. Grafting people with prior experience with other R&D units also occurs on occasion when the project is initiated by top management or when the project managers have a strong connection with the other R&D units. These two approaches make working across R&D units possible. Grafting people from local technology users occurs when an LTU and the national laboratories are engaged in a collaborative project.

6.2. A FRAMEWORK FOR KNOWLEDGE FLOWS WITHIN THE NATIONAL INNOVATION SYSTEM

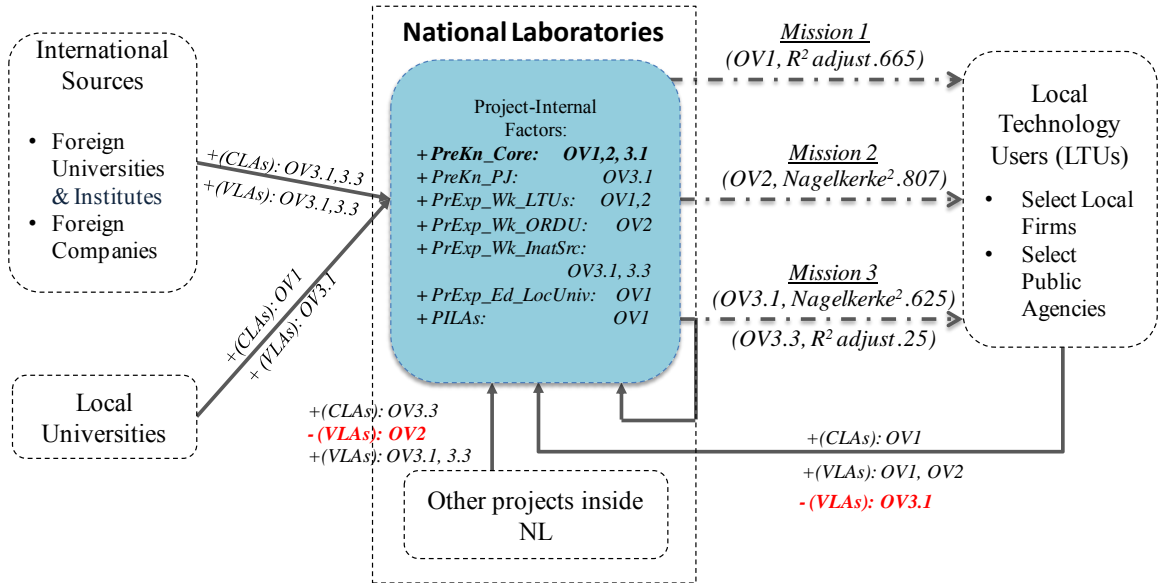


Figure 6.1: Knowledge flows within the national innovation system, which pertain to the national laboratories.

Figure 6.1 illustrates the overarching conclusion of this dissertation—the validation of the theoretical framework that was created from the literature review in chapter 2. Figure 6.1 is an extension of figure 2.5. It shows that all aspects of the theoretical framework from chapter 2, which is presented in section 2.5, have been validated empirically by confirming the majority of the hypotheses from chapter 3. Figure 6.1 identifies which path for knowledge inflow contributes to which laboratory mission, which form of internal knowledge contributes to which mission, as well as the valence of these contributions. Figure 6.1 also denotes the valence of the interactions between the various knowledge inflows and the various forms of internal knowledge, as well as the output

variables that they impact. Finally, figure 6.1 illustrates the complexity of the knowledge flows within the national innovation system that pertain to the national laboratories of a technology latecomer country. It suggests that the national laboratories cannot just implement one or two broad policy initiatives that will impact performance on a global scale without inducing collateral effects at the micro-level.

The results of my dissertation research show that the impact on performance of knowledge flows within the national innovation system that pertains to the national laboratories is nuanced and differentiated. For example, figure 6.1 suggests that the managers within the national laboratories have levers with which they can impact the performance of their institution and influence the national innovation system in the long run. One particular lever can impact more than one output variable, and one specific output variable can be influenced by more than one lever. The national laboratory system consequently consists of *multiple subsystems*, where each subsystem is associated with *a particular mission* or with *a specific source of knowledge*. This system will henceforth be referred to as the National Laboratories Knowledge Management System (NLKMS), and its subsystems will henceforth be called the National Laboratories Knowledge Management Subsystems (NLKMSS).

6.3 SELECTIVE ABSORPTION OF KNOWLEDGE

Cohen and Levinthal have argued that “the ability of a firm to recognize the value of new, external information, assimilate it, and apply it to commercial ends is critical to its innovative capabilities. [They] label this capability a firm's absorptive capacity and suggest that it is largely a function of the firm's level of prior related knowledge” (W. M. Cohen & Levinthal, 1990, p. 128). In this dissertation, I have conducted research that has analyzed absorptive capacity in the environment of the national laboratories, using individual project groups as my unit of analysis. The results, which have been presented in chapter 5, suggest that absorptive capacity is an important component of managing knowledge within the national laboratory system of a technology latecomer country. In addition, I have found that capacity of R&D project groups within the national laboratories to absorb knowledge from external sources is not just related to prior related knowledge; it is also a function of the source of external knowledge, the knowledge pathway into the project group; the source of complementary or substitutive knowledge that resides within the project group; and the mission to which the knowledge contributes.

The sparse interaction matrix in table 5.20 suggests that the capacity to absorb knowledge is quite selective. Only 39 of the 192 possible permutations for mechanisms to absorb knowledge from external sources actually have a statistically significant impact on performance. Yet, as table 5.21 shows, the statistical signals for the interactions, regardless whether they are substitutive or complementary, are relatively strong. This gives the managers of the national laboratories a toolkit of micro-levers with which they

can selectively target a specific aspect of performance that they want to improve. Individual project groups can thus contribute to the performance of the national laboratories by pulling the appropriate lever.

It should also be noted that the statistically significant interactions do not occur in a random fashion. A few very distinct patterns of interactions have been identified in section 5.5.2. These patterns provide insight into the structure of the knowledge subsystems of the National Laboratories Knowledge Management System, whose existence has been proposed in figure 6.2.

6.4 MISSION-SPECIFIC CONCLUSIONS

6.4.1 Conclusions Pertaining to User Satisfaction (Mission 1)

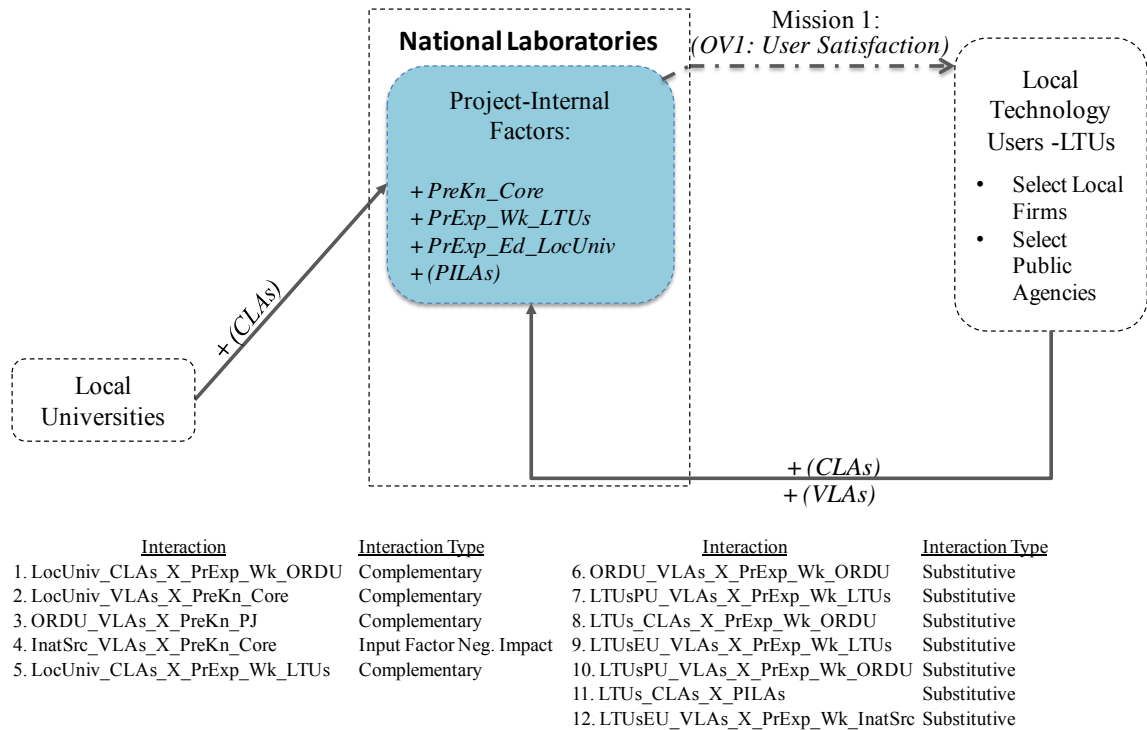


Figure 6.2: The knowledge management subsystem of the National Laboratory Knowledge Management System that contributes to user satisfaction

Figure 6.2 summarizes all the results that pertain to hypotheses 1a, 2a, 3a and 4a in section 5.4, as well as the results from the relative ranking of correlation coefficients that pertain to OV1 in section 5.4.5 and the results of running the interaction model for OV1 in section 5.5. Figure 6.2 depicts everything pertaining to knowledge flows within the national laboratory system and their impact on user satisfaction that my research has been

able to verify to date at a level of statistical significance of $p < 0.05$. I consequently propose that figure 6.2 represents a framework, which characterizes the subsystem of the national laboratories that governs user satisfaction.

The framework in figure 6.2 suggests that user satisfaction is primarily driven by three kinds of knowledge inflow from two exogenous sources: contextual and vicarious feedback from local technology users and contextual learning from local universities. Various internal sources of knowledge such as prior knowledge about the core technology, grafting people with prior work experience at LTUs, prior education at local universities and project-internal learning activities also contribute positively to user satisfaction. In the interaction model, vicarious learning with international sources is negatively correlated to user satisfaction at a level of statistical significance of $p < 0.05$. (There is no statistically significant correlation between vicarious learning with international sources and user satisfaction in the integrated model.) Figure 6.2 also lists all the interactions pertaining to user satisfaction that are complementary (are positively correlated to OV1) or substitutive (negatively correlated to OV1). One interaction – the one between vicarious learning with international sources and prior knowledge about the core technology (interaction no.4) – is negatively complementary; it decreases the negative impact that vicarious learning with international sources has on the user satisfaction.

The following conclusions can be drawn from figure 6.2.

Conclusion 6.4.1-1: *Engagement with local technology users increases user satisfaction.*

All input factors pertaining to engagement with LTUs (VLAs with LTUs that have production units, VLAs with end users, CLAs with LTUs of all kinds and grafting people with work experience at LTUs) had a strong positive correlation with user satisfaction. This conclusion is consistent with prior findings related to user innovation (e.g., von Hippel, 1988, 1989, 2005).

Conclusion 6.4.1-2: *When it comes to user satisfaction, at least one of the following is true: 1) internal knowledge gained from project-internal learning activities (interaction no. 11), or from grafting people with prior experience at other R&D project groups within the NLS (see interactions 6, 8 & 10), LTUs (see interactions 7 & 9), and international sources (see interaction no. 12) are substitutes for external learning with LTUs; or 2) the project group suffers from the Not-Invented-Here syndrome.*

Interviews with the project managers suggest the grafting someone with prior work experience at LTUs into the project group is a true substitute for engaging in external learning with the LTUs, vicarious learning in particular (see interactions 7 & 9). The grafted person has engaged in vicarious learning activities at the LTU and brings the tacit knowledge that he/she has acquired through VLAs into the project group, where it is shared with the other team members through prolonged socialization. I call this phenomenon *vicarious learning by proxy*; it has been observed in the semiconductor industry, where technology supplier firms hire senior technical personnel from leading-edge chipmakers as marketing representatives (Weber, 2002; Yang *et al.*, 2012).

The interviews with the project managers suggest that the other ostensible substitution effects could be caused by NIH. For example, project-internal learning might make the project group feel that it has no need to engage in contextual learning about the LTUs (interaction no. 11). Furthermore, grafting people with work experience at international sources (interaction no. 12), or other R&D project groups (see interactions 6 & 10), into the project group may make the project group feel it no longer needs to engage in vicarious learning with the LTUs. I consequently propose the following for further study:

Proposition 6.4.1-1: Project-internal learning activities (see interaction no.11) and grafting people with work experience at international sources (see interaction no.12) or other R&D project groups within the national laboratories (see interactions 6, 8 & 10), can be a source of the Not-Invented-Here syndrome.

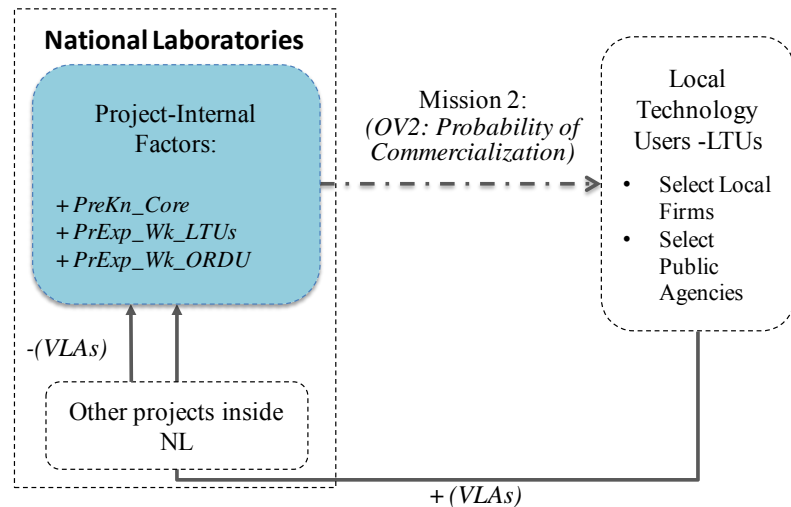
Conclusion 6.4.1-3: *Factors that enhance user satisfaction are local.* All factors that increase user satisfaction have their origins within Thailand. The sources of knowledge that contribute to user satisfaction are local technology users, local universities and the R&D project groups themselves. The channels for inflow vary. Knowledge from LTUs enters the project group via VLAs, CLAs and grafting. Knowledge from local universities comes from contextual learning or from team members who were educated there. Prior knowledge about the core technology exists in the project group at the outset of the project. Knowledge from international sources has no direct impact on user satisfaction.

Interviews with the project managers support this conclusion, and they yield the following explanation of why user satisfaction has local roots. The LTUs, to a large

degree, drive development at the national laboratories because they do not have the time, the expertise and the financial resources to do it themselves. The LTUs primary mission is to serve the customers in Thailand, and most of the production units of the LTUs are in Thailand. It is therefore very efficient for the LTUs to procure, allocate and coordinate resources locally. Some LTUs do have significant export businesses, but these tend to provide products with a relatively low value added. Most of the LTUs have not yet made the investments that would allow them to generate high value-added products that could compete with the products from developed nations.

6.4.2 Conclusions Pertaining to Commercialization (Mission 2)

Figure 6.3 summarizes all the results that pertain to hypotheses 1b, 2b, 3b and 4b in section 5.4, as well as the results from the relative ranking of correlation coefficients that pertain to OV2 in section 5.4.5 and the results of running the interaction model for OV2 in section 5.5. Figure 6.3 depicts everything pertaining to knowledge flows within the national laboratory system and their impact on the probability of commercialization that my research has been able to verify to date at a level of statistical significance of $p < 0.05$. I consequently propose that figure 6.3 represents a framework, which characterizes the subsystem of the national laboratories that governs commercialization.



<u>Interaction</u>	<u>Interaction Type</u>	<u>Interaction</u>	<u>Interaction Type</u>
13. LTUs_CLAs_X_PrExp_Wk_LTUs	Complementary	19. LTUsEU_VLAs_X_PreKn_Core	Substitutive
14. ORDU_VLAs_X_PreKn_Core	Input Factor Neg. Impact	20. LTUsPU_VLAs_X_PreKn_Core	Substitutive
15. InatSrc_CLAs_X_PreKn_Core	Complementary	21. LTUs_CLAs_X_PreKn_Core	Substitutive
16. ORDU_VLAs_X_PreKn_PJ	Input Factor Neg. Impact	22. LTUs_CLAs_X_PILAs	Substitutive
17. LocUniv_CLAs_X_PrExp_Wk_LTUs	Complementary	23. InatSrc_VLAs_X_PreKn_Core	Substitutive
18. LocUniv_CLAs_X_PreKn_PJ	Complementary	24. InatSrc_VLAs_X_PILAs	Substitutive

Figure 6.3: The knowledge subsystem of the national laboratory system that contributes to commercialization of technology

The framework in figure 6.3 suggests that the probability of commercialization is primarily driven by two kinds of knowledge inflow from two exogenous sources: vicarious feedback from local technology users, which is positively correlated to OV2, and vicarious learning from other R&D project groups within the national laboratories, which is negatively correlated to OV2. Various internal sources of knowledge such as prior knowledge about the core technology, grafting people with prior work experience at LTUs and grafting people with prior work experience at other R&D groups within the national laboratories also contribute positively to the probability of commercialization. Figure 6.3 also lists all the interactions pertaining to the probability of commercialization that are complementary (positively correlated to OV2) or substitutive (negatively

correlated to OV2). Two interactions (14 & 16) are negatively complementary; the moderating factor in these interactions decreases the negative impact that vicarious learning with other R&D project groups has on the probability of commercialization.

The data from Chapter 5 suggest that, like user satisfaction, commercialization is driven, to a large degree, by local technology users. In particular, the probability of commercialization is enhanced if knowledge is acquired through vicarious learning or through grafting someone with work experience at an LTU. Yet, the interactions between those sources of knowledge have no significant impact on commercialization. I consequently draw the following conclusions for VLAs and their impact on commercialization.

Conclusion 6.4.2-1: *Engaging with local technology users through VLAs or vicarious learning by proxy enhances the project group's ability to commercialize. However, these activities are not substitutes.*

The data from section 5.5 show that prior knowledge about the core technology by itself enhances the probability of commercialization. Yet, if anything, prior knowledge about the core technology acts as a substitute for VLAs with LTUs. Interviews with the project managers suggest that prolonged experience in working on the core technology gives the project team a better understanding of user needs. This leads to the following conclusion.

Conclusion 6.4.2-2: *When it comes to commercialization, prior knowledge about the core technology is a true substitute for vicarious learning activities with LTUs (see interactions 19 & 20).*

However, given that NIH is a possible alternative for true substitution, I suggest that the following proposition be tested by further study.

Proposition 6.4.2-1: Project managers in the national laboratories, who overwhelmingly come from an engineering background, have a world view that is driven by technology push. Their view of the market for the technology that is under development could consequently be biased towards technology push. Prior knowledge about the core technology could therefore diminish the project group's capacity to absorb contextual knowledge about LTUs and their interest to engage in vicarious learning with LTUs (see interactions 19 through 21).

Contextual learning about local technology users has no statistically significant impact on the probability of commercializing a technology by itself. The interviews with project managers provide the following explanation for this result. Most of the knowledge that is required for commercialization is tacit and thus cannot be transferred readily by CLAs—either externalization of knowledge or vicarious learning is inherently required (Nonaka, 1994; Szulanski, 1996). Nonetheless, vicarious learning by proxy could in principle enhance any positive impact that CLAs with LTUs have (see interaction no.13). The following conclusion can consequently be drawn.

Conclusion 6.4.2-3: *Grafting people with prior work experience at an LTU into the project group enhances the positive impact on commercialization of contextual learning about LTUs (see interaction no. 13).* Interviews with the project managers suggest that the people who were grafted into the project group help with the interpretation of data that is acquired through contextual learning activities.

Commercialization of technology requires diversity of knowledge, some of which may be found in ORDUs. For example, the data from interaction model suggests that grafting people with prior work experience at other R&D project groups tends to enhance commercialization of technology. By contrast, vicarious learning with other R&D project groups has a negative impact on commercializing the technology under development. Prior knowledge about the core technology or externalize prior knowledge about subject matter pertaining to the project decreases the negative impact that vicarious learning with ORDUs has on commercialization of technology (see interactions 14 & 16). The interaction between vicarious learning with ORDUs and grafting people with prior work experience at ORDUs into the project group is not statistically significant.

One may infer from the data in chapter 5 that project-internal knowledge is a necessary, but insufficient condition for developing technology for commercialization. Additional knowledge that is required for commercialization resides within other R&D project groups, particularly in project groups who are currently commercializing technology or have done so in the past. This knowledge can either be brought into the project group by vicarious learning with other R&D units within the national laboratories, or through vicarious learning by proxy, i.e. by grafting people with prior work experience at ORDUs

into the project group. In the former case, the members of the project group exchange ideas about commercialization with their peers from other project groups. In the latter case, some of these peers from these ORDUs are brought into the project group prior to the inception of the project.

Data from the interviews with project managers provide an explanation as to why vicarious learning with other R&D project groups in the national laboratories is detrimental to commercialization, whereas the grafting people with prior work experience at other R&D project groups enhances it. Project managers consistently stressed time pressure as an important factor in commercialization of technology in their interviews. Some of them suggested that the LTUs perceive the market windows for the products that use technology that is under development at the national laboratories is very short. The LTUs make more money on these products if the NLs deliver the technology sooner. The R&D project groups within the NLs consequently need to integrate any missing crucial knowledge in a timely manner. Bringing this knowledge into the project group and spreading it around before the outset of the project (e.g., Huber, 1991) fulfills this requirement. Engaging in VLAs with ORDUs does not because the socialization associated with VLAs is inherently time-consuming and distracts from vital activities in a deadline-driven project (Nonaka, 1994; Szulanski, 1996; Hatch & Mowery, 1998). VLAs with ORDUs may even delay the actual delivery date for the technology under development. Furthermore, bringing a person with prior work experience at another R&D unit into the project group before the outset of the project may enhance that person's commitment of to the project.

The following conclusion about integrating knowledge from other R&D units within the national laboratories into the project group can consequently be drawn.

Conclusion 6.4.2-3: *If commercialization of technology occurs under time pressure, then grafting rather than vicarious learning is the better choice for bringing tacit knowledge from other R&D units into the project group.*

The data in chapter 5 suggest that commercialization, like user satisfaction, has primarily local roots. The following conclusion regarding the impact of local knowledge on the ability to commercialize technology can be drawn.

Conclusion 6.4.2-4: *Factors that enhance the probability of commercialization are local.*

All factors that increase the probability of commercialization have their origins within Thailand. The sources of knowledge that enhance commercialization of technology are local technology users, local universities and the R&D project groups themselves. The channels for inflow differ slightly from those that enhance user satisfaction. Knowledge from LTUs that enhances commercialization enters the project group via VLAs and grafting, but not CLAs. Local universities are less important for commercialization of technology than they are for user satisfaction, but prior externalized knowledge about the project and grafting people with prior work experience at LTUs are complementary to whatever impact local universities have on commercialization (see interactions 18 & 17). Knowledge from international sources by itself has no direct impact on commercialization of technology. However, the interaction model suggests that prior knowledge about the core technology (see interaction no.23) and project-internal learning

activities (see interaction no.24) are potential substitutes for whatever impact international sources have on commercialization. The interviews with the project managers gave no indication as to whether these sources of internal knowledge are true substitutes or whether they are symptoms of NIH.

Interviews with the project managers suggest that local sources of knowledge primarily contribute to commercialization of technology for similar reasons similar to why they contribute to user satisfaction. The LTUs, to a large degree, drive commercialization of technology that is developed at the national laboratories because they do not have the time, the expertise and the financial resources to develop the technology themselves. The LTUs primary mission is to serve the customers in Thailand, and most of the production units of the LTUs are in Thailand. It is therefore very efficient for the LTUs to procure, allocate and coordinate resources locally. Some LTUs do have significant export businesses, but these tend to provide products with a relatively low value added. Most of the LTUs have not yet made the investments that would allow them to generate high value-added products that could compete with the products from developed nations.

6.4.3 Conclusions Pertaining to a Long-term R&D Capability (Mission 3)

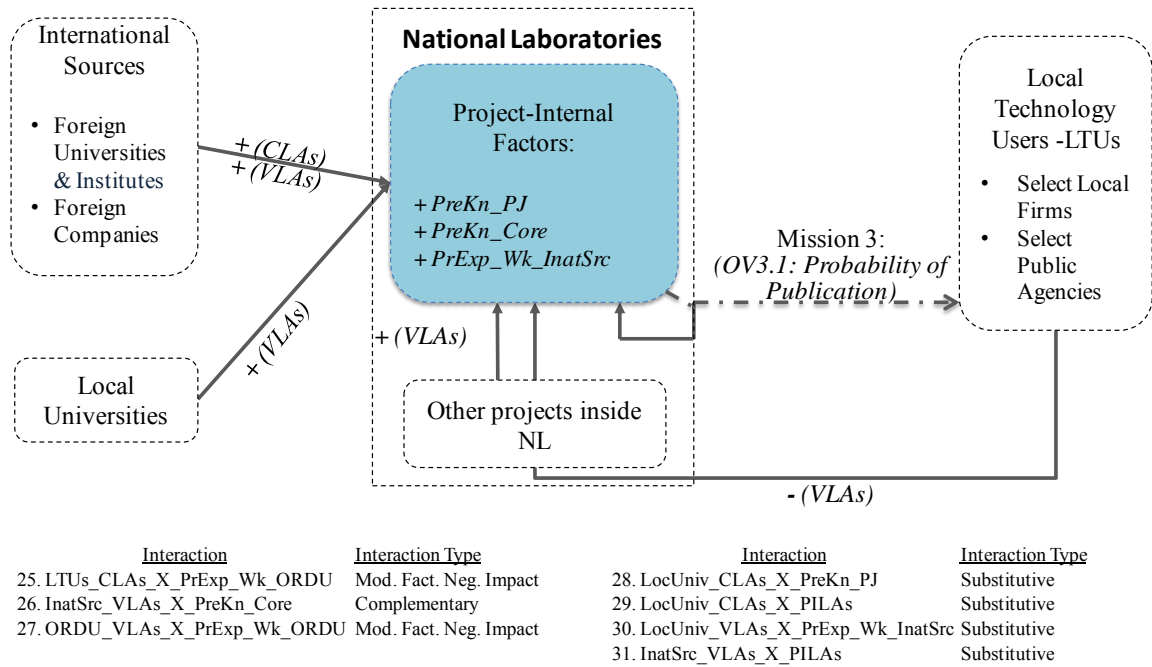


Figure 6.4: The knowledge management subsystem of the National Laboratory Knowledge Management System that affects the probability of generating a publication from a particular project

Figure 6.4 summarizes all the results that pertain to hypotheses 1c, 2c, 3c and 4c in section 5.4, as well as the results from the relative ranking of correlation coefficients that pertain to OV3.1 in section 5.4.5 and the results of running the interaction model for OV3.1 in section 5.5. Figure 6.4 depicts everything pertaining to knowledge flows within the national laboratory system and their impact on the probability of publication that my research has been able to verify to date at a level of statistical significance of $p < 0.05$. I consequently propose that figure 6.4 represents a framework, which characterizes the subsystem of the national laboratories that governs the probability of publication.

The framework in figure 6.4 suggests that the probability of publication is primarily driven by five kinds of knowledge inflow from four exogenous sources: contextual learning about and vicarious learning with international sources, vicarious learning with local universities, vicarious learning with other R&D project groups within the national laboratories and vicarious feedback from local technology users. The first four of these knowledge inflows have a positive impact on the probability of publication, whereas the impact of VLAs with LTUs is negative. Various internal sources of knowledge such as prior externalized knowledge about subject matter pertaining to the project, prior knowledge about the core technology and grafting people with prior work experience at international sources contribute positively to the probability of publication.

In the interaction model, grafting people with work experience at other R&D units within the national laboratories into the project group is negatively correlated to the probability of publication at a level of statistical significance of $p=0.88$; it has no statistical significance in the integrated regression model. Figure 6.4 also lists all the interactions pertaining to probability of publication that are complementary (positively correlated to OV3.1) or substitutive (negatively correlated to OV3.1). Two interactions (no. 25 & 27) are negatively complementary; the knowledge inflow ameliorates the negative impact that grafting people with work experience at other R&D project groups within the national laboratories has on the probability of publication.

According to the ranking of correlation coefficients in section 5.4.5, the external sources of knowledge that have the biggest positive impact on the probability of publication are international sources of knowledge, local universities and other R&D project groups

within the national laboratories. The most important internal sources of knowledge that have a positive impact on the probability of commercialization are prior externalized knowledge about the project, prior knowledge about the core technology, and prior work experience at international sources. Some of the interactions between these factors are substitutive or complementary; others are statistically insignificant.

The data from sections 5.4 and 5.5 lead to the following conclusion regarding the impact of knowledge from international sources on the probability of publication.

***Conclusion 6.4.3-1:** In order to increase the probability of publication, knowledge from international sources can be brought into the project group through vicarious learning or by proxy through grafting people with prior work experience at international sources. However, grafting people with work experience international sources is not a substitute for vicarious learning with international sources.*

The interviews with the project managers have generated significant insight into the organizational processes behind this conclusion. The reliance on international sources of knowledge results from the realization that the cutting edge of science and technology is still overseas. As a consequence, the project groups within the national laboratories orient themselves toward international sources. They identify the most important sources and their critical activities through contextual learning. They subsequently engage in vicarious learning activities with the international sources to bring advanced foreign knowledge and essential capabilities into the project group. Prior knowledge about the core technology enhances the effectiveness of this effort (see interaction no. 26). Project-

internal learning activities ostensibly act as a substitute for vicarious learning with international sources (see interaction no. 31), but the interviews revealed no explanation as to why this could be. The following alternative proposition must therefore be considered for further study.

Proposition 6.4.3-1: *When it comes to generating publications, project-internal learning activities cause the Not-Invented-Here syndrome within project groups; they may simply act as a barrier to knowledge inflow from international sources (see interaction no. 31).*

The data from sections 5.4 and 5.5 lead to the following conclusion regarding the impact of knowledge from international sources on the probability of publication.

Conclusion 6.4.3-2: *Prior knowledge about the core technology enhances the positive impact of vicarious learning from international sources on the probability of publication (see interaction no.26).*

This conclusion is in alignment within the classic literature on absorptive capacity (*e.g.*, W. M. Cohen & Levinthal, 1990). Prior knowledge about the core technology enables the project group to absorb related knowledge through vicarious learning with international sources. Once again, the realization that most advanced science and technology resides outside the national innovation system drives the need to engage in VLAs with international sources.

The data from sections 5.4 and 5.5 show that vicarious learning with local technology users has the opposite effect on the probability of publication than it does on the probability of commercialization. This leads to the following conclusion.

Conclusion 6.4.3-3: *Vicarious learning with local technology users has a detrimental impact on the probability of generating publications.* Local technology users are deadline driven, and they tend to focus on the near term. This outlook distracts from research and development that generates publications, which takes time because it requires a greater degree of scientific evidence. Furthermore, engagement with LTUs is on a lower technical level; it does not require the advanced technical knowledge that leads to publications.

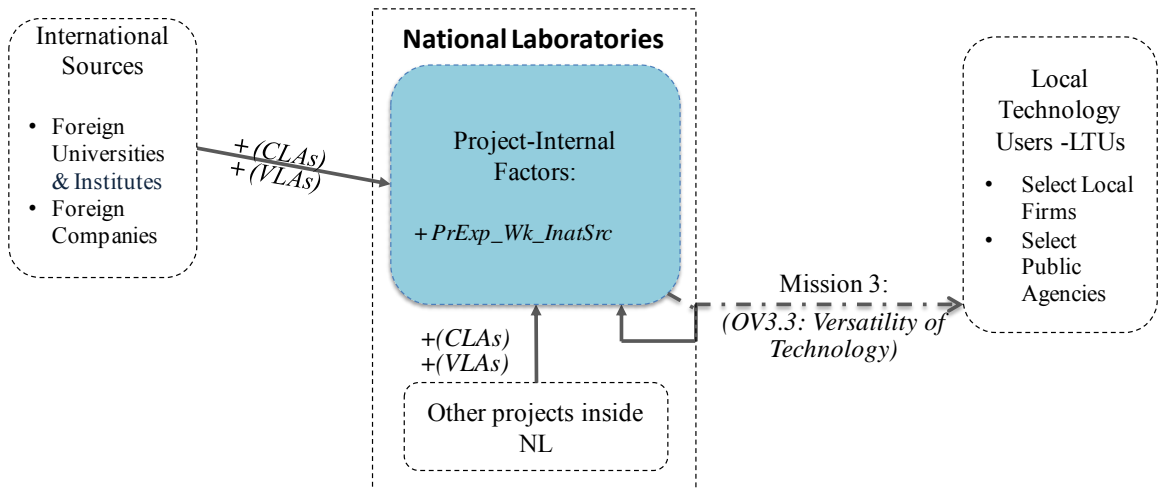
The data in sections 5.4 and 5.5 imply that, when it comes to publications, vicarious learning with local universities constitutes an important source of external knowledge.

Conclusion 6.4.3-4: *R&D project groups within the national laboratories engage in vicarious learning with local universities when they have insufficient in house capabilities for developing a technology on their own, and engaging in VLAs with local universities tends to lead to joint publications.* The interviews with project managers lead to the following conclusion as to why that might be. For example, a biotechnology that was developed at the national laboratories may undergo clinical tests at a local medical school.

The data in sections 5.4 and 5.5 imply that prior work experience at international sources could act as a substitute for knowledge inflow from local universities (see interaction no. 30). Interviews with project managers suggest that such a substitution could come from an exchange program with an international source of knowledge such as well-known foreign university, foreign research institute or an R&D facility that is owned by a foreign corporation.

According to section 5.4.6, prior explicit or externalized knowledge is the most prominent project-internal source of knowledge when it comes to the probability of publication. Interviews with project managers have led to the following conclusion as to why that is.

Conclusion 6.4.3-5: *Prior explicit knowledge of subject matter pertaining to the project is required to generate a publication about the project, and prior explicit knowledge tends to come in the form publications. The skill to generate publications is already present at the outset of the project. Prior publication helps with future publication, which leads to the establishment of a publication culture.*



<u>Interaction</u>	<u>Interaction Type</u>	<u>Interaction</u>	<u>Interaction Type</u>
32. LTUsEU_VLAs_X_PILAs	Complementary	36. LTUs_CLAs_X_PreKn_PJ	Substitutive
33. LTUs_CLAs_X_PILAs	Complementary	37. InatSrc_CLAs_X_PILAs	Substitutive
34. LocUniv_CLAs_X_PrExp_Wk_ORDU	Mod. Fact. Neg. Impact	38. LTUs_CLAs_X_PrExp_Wk_InatSrc	Substitutive
35. ORDU_VLAs_X_PreKn_PJ	Complementary	39. LocUniv_CLAs_X_PILAs	Substitutive

Figure 6.5: The knowledge management subsystem of the National Laboratory Knowledge Management System that contributes to versatility of technology

Figure 6.5 summarizes all the results that pertain to hypotheses 1c, 2c, 3c and 4c in section 5.4, as well as the results from the relative ranking of correlation coefficients that pertain to OV3.3 in section 5.4.5 and the results of running the interaction model for OV3.3 in section 5.5. Figure 6.5 depicts everything pertaining to knowledge flows within the national laboratory system and their impact on versatility of technology that my research has been able to verify to date at a level of statistical significance of $p < 0.05$. I consequently propose that figure 6.5 represents a framework, which characterizes the subsystem of the national laboratories that governs versatility of technology.

The framework in figure 6.5 suggests that versatility of technology is primarily driven by four kinds of knowledge inflow from two exogenous sources: contextual learning about

and vicarious learning with international sources; and contextual learning about and vicarious learning with other R&D project groups within the national laboratories. All four of these knowledge inflows have a positive impact on versatility of technology. One internal source of knowledge also has a positive impact on versatility of technology: grafting people with prior work experience at international sources.

Figure 6.5 also lists all the interactions pertaining to versatility of technology that are complementary (positively correlated to OV3.3) or substitutive (negatively correlated to OV3.3). One interaction is negatively complementary; contextual learning about local universities enhances the negative impact that grafting people with work experience at other R&D project groups within the national laboratories has on versatility of technology (see interaction no. 34). However, the negative impact of ORDUs on versatility of technology is only statistically significant at the level of $p < 0.05$ in the interaction model.

According to the results from section 5.4, the sources of knowledge that have the biggest impact on the versatility of the technology under development come from outside the national innovation system. Grafting people with prior work experience at international sources and vicarious learning with international sources constitute the two factors that have the largest positive correlation to versatility of technology, but the interaction between these two factors has no statistically significant impact on versatility of technology. Contextual learning about international sources also has a positive impact on versatility of technology, but the interaction between contextual learning and grafting

people with work experience at international sources is statistically insignificant as well. These observations lead to the following conclusion.

Conclusion 6.4.3-6: *In order to increase the versatility of the technology under development, knowledge from international sources can be brought into the project group through vicarious learning or by proxy through grafting people with prior work experience at international sources.*

The interviews with the project managers suggest that international sources play an important role in generating ideas for applications. In particular, they generate insight into how technologies that are related to the technology under development are applied in other countries.

The second most important source of knowledge pertaining to versatility of technology is other R&D project groups within the national laboratories. According to interviews with the project managers, the primary role of engaging with these other project groups is to obtain complementary knowledge. If the project groups that interact with each other happen to design for different strategic objectives in different markets, then each team is more likely to learn about another application for their technology, and the combinative capabilities (Kogut & Zander, 1992) of the national laboratories as a whole are enhanced. The following conclusion regarding versatility of technology can thus be drawn.

Conclusion 6.4.3-7: *Engaging in external learning with other R&D project groups through VLAs or CLAs leads to new applications for the technology under development.*

6.5 ORGANIZATIONAL AMBIDEXTERITY AND MISSION ALIGNMENT

6.5.1 Alignment of Output Variables

Chapter five presented much evidence that the three basic missions of the national laboratories are not necessarily aligned. For example, the correlation matrix in table 5.9 shows a positive correlation between OV1 and OV2 and a positive correlation between OV3.1 and OV3.3. However, OV3.1 is inversely correlated with OV1 and OV2. This suggests that mission 1 (user satisfaction) is well aligned with mission 2 (commercialization), and that the two remaining output variables for mission 3 (building an R&D capability for the future of the country) are well aligned. The inverse correlation between OV3.1 on the one hand and OV1 and OV2 on the other hand implies misalignment between mission 3 on the one hand and missions 1 and 2 on the other hand.

6.5.2 Alignment of Factors

The correlations between the output variables are consistent with what was observed about the input factors and moderating factors. With one exception, the following rules seem to hold for all factors in the correlation matrix, the knowledge inflow baseline, the project group baseline, the intra-organization baseline and the integrated model. The rules also hold in the interaction model, albeit with an additional exception.²⁹

²⁹ In the interaction model project-internal learning activities are positively correlated to user satisfaction and to versatility of technology (with $p < 0.05$). In the integrated model, project-internal learning activities

Rule [1, 2]: A factor that is positively correlated to user satisfaction (mission 1) can be *positively* correlated to the probability of commercializing a technology (mission 2), or *not* correlated to the probability of commercializing a technology (mission 2), but *not negatively* correlated to the probability of commercializing a technology (mission 2).

Rule [1, 3]: A factor that is positively correlated to user satisfaction (mission 1) can be *negatively* correlated to versatility of a technology or the probability of generating a publication (mission 3), or *not* correlated to versatility of a technology or the probability of generating a publication (mission 3), but *not positively* correlated to versatility of a technology or the probability of generating a publication (mission 3)

Rule [2, 3]: A factor that is positively correlated to the probability of commercializing a technology (mission 2) can be *negatively* correlated to versatility of technology or the probability of generating a publication (mission 3), or *not* correlated to versatility of technology or the probability of generating a publication (mission 3), but *not positively* correlated to versatility of technology or the probability of generating a publication (mission 3).

Rule [3, 3]: A factor that is positively correlated to the versatility of the technology under development (mission 3) can be *positively* correlated to the probability of

are correlated to user satisfaction with $p < 0.05$. There is no statistically significant correlation between project-internal learning activities and versatility of technology.

generating a publication (mission 3), or *not* correlated to the probability of generating a publication (mission 3), but *not negatively* correlated to the probability of generating a publication (mission 3).

One can infer from the above rules that factors that help the national laboratories succeed at missions 1 and 2 can interfere with Mission 3, and conversely. This leads to the following conclusions.

Conclusion 6.5.2-1: Rule [3, 3] reinforces the notion that *the output metrics for mission 3 (building an R&D capability for the future of the country) are well aligned.*

Conclusion 6.5.2-2: Rule [1, 2] implies that *mission 1 (user satisfaction) and mission 2 (commercializing technology) align well with each other.*

Conclusion 6.5.2-3: According to rules [1, 3] and [2, 3], *mission 3 (building an R&D capability for the future of the country) is misaligned with mission 1 (user satisfaction) and mission 2 (commercializing technology) at all levels.*

Prior knowledge about core technology is the exception to the above rules in the correlation matrix and in all pertinent regression models. Prior knowledge about the core technology is positively correlated to user satisfaction, the probability of commercializing a technology and the probability of generating a publication. It is not correlated to the versatility of the technology under development.

6.5.2 Organizational Ambidexterity

Organizational Ambidexterity has been defined as balancing the need to exploit against the need to explore (Tushman & O'Reilly, 1996). It is a well-known challenge in most innovation-driven firms (Tushman & O'Reilly, 1996; O'Reilly & Tushman, 2004; Gibson & Birkinshaw, 2004; Raisch & Birkinshaw, 2008; O'Reilly & Tushman, 2008; Ambos *et al.*, 2008; Simsek, 2009; Raisch *et al.*, 2009; Andriopoulos & Lewis, 2009; Taylor & Helfat, 2009; Rothaermel & Alexandre, 2009; Cao *et al.*, 2009; Jansen *et al.*, 2009; Mom *et al.*, 2009; O'Reilly & Tushman, 2011), and has been observed in the university environment (Y.-C. Chang *et al.*, 2009). However, it has yet to be studied or even identified in national laboratories.

Organizational ambidexterity presents a framework that can explain the alignment and misalignment of the output variables that have been studied as part of this dissertation. For example, mission 3 (building an R&D capability) is designed to improve the national laboratories ability to explore. Alignment between OV3.1 and OV3.3 consequently supports the ambidexterity framework. Mission 1 (user satisfaction) and mission 2 (commercialization) are clearly exploitative. From the point of view of ambidexterity alignment between these two missions is expected. The ambidexterity paradigm also suggests that there should be tension between the exploration-oriented missions the exploitative missions, and there is. This leads to the following conclusion.

Conclusion 6.5.3-1: The national laboratories face an ambidexterity challenge.

6.6 CONCLUSIONS ABOUT KNOWLEDGE INFLOWS AND INTERNAL KNOWLEDGE

In sections 6.4, I drew conclusions that specifically concerned the three fundamental missions of the laboratories, and in section 6.5, I showed how these missions were either aligned or misaligned. In this section, I look at the national laboratory system from the point of view of knowledge inflow and internal knowledge, and I compare the relative impact that these two forms of knowledge have on performance.

6.6.1 Conclusions about Knowledge Inflows.

In sections 3.1 through 3.4, I discussed the state of knowledge about knowledge inflows as it has been published in the academic literature, and I respectively proposed models for knowledge inflows from other R&D project groups, from local universities, from local technology users and from international sources in these sections of my dissertation. Schematics for these models were depicted in figures 3.2, 3.3, 3.4, and 3.5, respectively. I also proposed hypotheses 1 through 4, respectively, to validate the models from sections 3.1 through 3.4. In section 5.4, I showed that most, but not all of these hypotheses were confirmed. In section 5.5, I revealed some key interactions that are associated with particular knowledge inflows. In this section, I combine the results from sections 5.4 and 5.5 with data from interviews with project managers to reach conclusions that pertain to knowledge inflows. I generate models of the knowledge subsystems of the national laboratory system that pertain to *specific knowledge inflows*, and I point out the *differences* between these models and the models that were originally proposed in

sections 3.1 through 3.4. Most of the commonalities have already been discussed in the section on *mission-specific conclusions* (6.4).

6.6.1.1 Conclusions Pertaining to Knowledge Inflows from Other R&D Project Groups within the National Laboratories

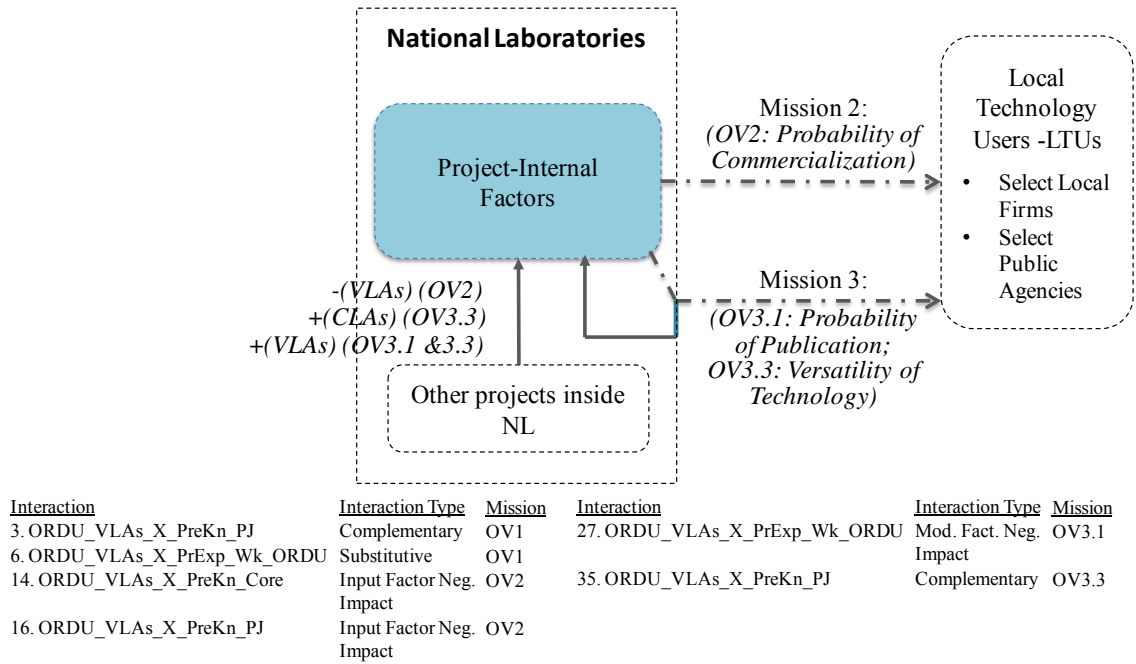


Figure 6.6: The knowledge management subsystem of the National Laboratory Knowledge Management System that pertains to knowledge inflows from other R&D project groups within the national laboratories

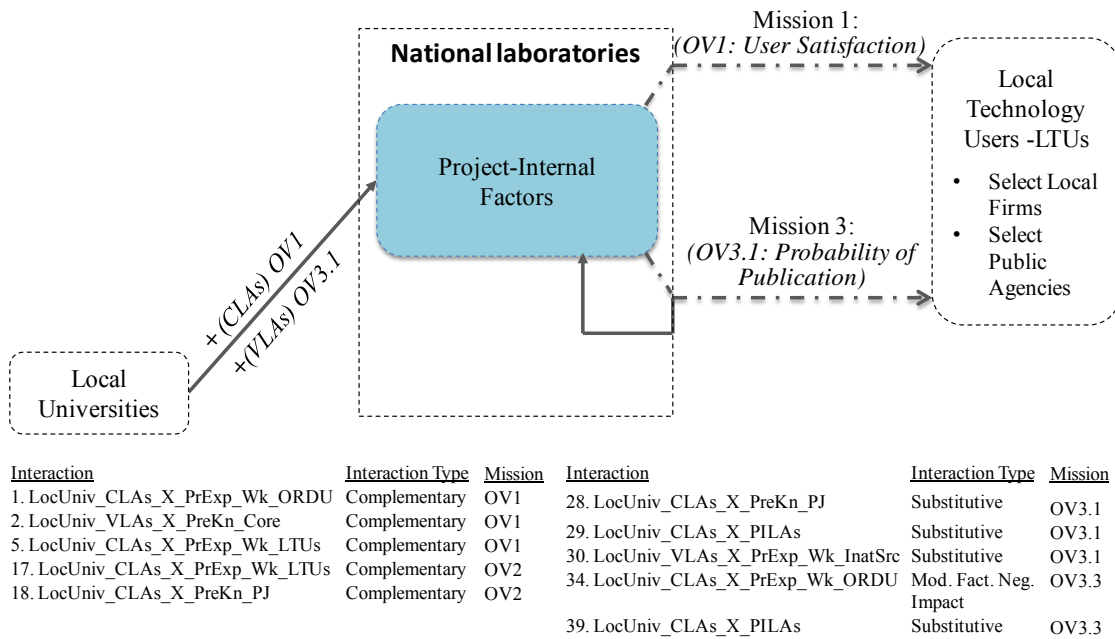
Figure 6.6 depicts the knowledge subsystem of the national laboratory system that pertains to knowledge inflows from other R&D project groups within the national laboratories. It is derived from the results of testing hypotheses 1a, 1b and 1c, as well as from the output of the interaction model in section 5.5. Figure 6.6 has much in common

with figure 3.2, but a comparison between the two figures also reveals some distinct differences. Figure 3.2 implies that both CLAs and VLAs with ORDUs should have a direct positive impact on all missions. However, in practice neither CLAs nor VLAs have a direct, significant impact on user satisfaction, and vicarious learning with ORDUs has a negative impact on the probability of commercialization (OV2). Only the interaction between vicarious learning with ORDUs and prior externalized knowledge about subject matter pertaining to the project has a positive impact on user satisfaction (see interaction no. 3). Nonetheless, in spite of these discrepancies, the existence of a subsystem of the national laboratories system that governs knowledge flows across R&D project groups within the national laboratories has been verified, and the model from figure 3.2 has been validated to a significant degree.

6.6.1.2 Conclusions Pertaining to Knowledge Inflows from Local Universities

Figure 6.7 depicts the knowledge subsystem of the national laboratory system that pertains to knowledge inflows from local universities. It is derived from the results of testing hypotheses 2a, 2b and 2c, as well as from the output of the interaction model in section 5.5. Figure 6.7 has much in common with figure 3.3, and a comparison between the two figures only reveals one distinct difference—external learning with local universities has no direct statistically significant impact on the probability of commercializing a technology. Only two interactions pertaining to local universities have a significant impact on the probability of commercialization—1) the interaction between contextual learning about local universities and grafting people with prior work experience at local technology users into the project group (see interaction no. 17); and 2)

the interaction between contextual learning about local universities and prior externalized knowledge about subject matter pertaining to the project (see interaction no. 18). In spite of this discrepancy, the existence of a subsystem of the national laboratories system that governs knowledge inflows from local technology users has been verified, and the model from figure 3.3 has been validated to a significant degree.



<u>Interaction</u>	<u>Interaction Type</u>	<u>Mission</u>	<u>Interaction</u>	<u>Interaction Type</u>	<u>Mission</u>
1. LocUniv_CLAs_X_PrExp_Wk_ORDU	Complementary	OV1	28. LocUniv_CLAs_X_PreKn_PJ	Substitutive	OV3.1
2. LocUniv_VLAs_X_PreKn_Core	Complementary	OV1	29. LocUniv_CLAs_X_PILAs	Substitutive	OV3.1
5. LocUniv_CLAs_X_PrExp_Wk_LTUs	Complementary	OV1	30. LocUniv_VLAs_X_PrExp_Wk_InatSrc	Substitutive	OV3.1
17. LocUniv_CLAs_X_PrExp_Wk_LTUs	Complementary	OV2	34. LocUniv_CLAs_X_PrExp_Wk_ORDU	Mod. Fact. Neg. Impact	OV3.3
18. LocUniv_CLAs_X_PreKn_PJ	Complementary	OV2	39. LocUniv_CLAs_X_PILAs	Substitutive	OV3.3

Figure 6.7: The knowledge management subsystem of the National Laboratory Knowledge Management System that pertains to knowledge inflows from local universities

6.6.1.3 Conclusions Pertaining to Knowledge Inflows from Local Technology Users

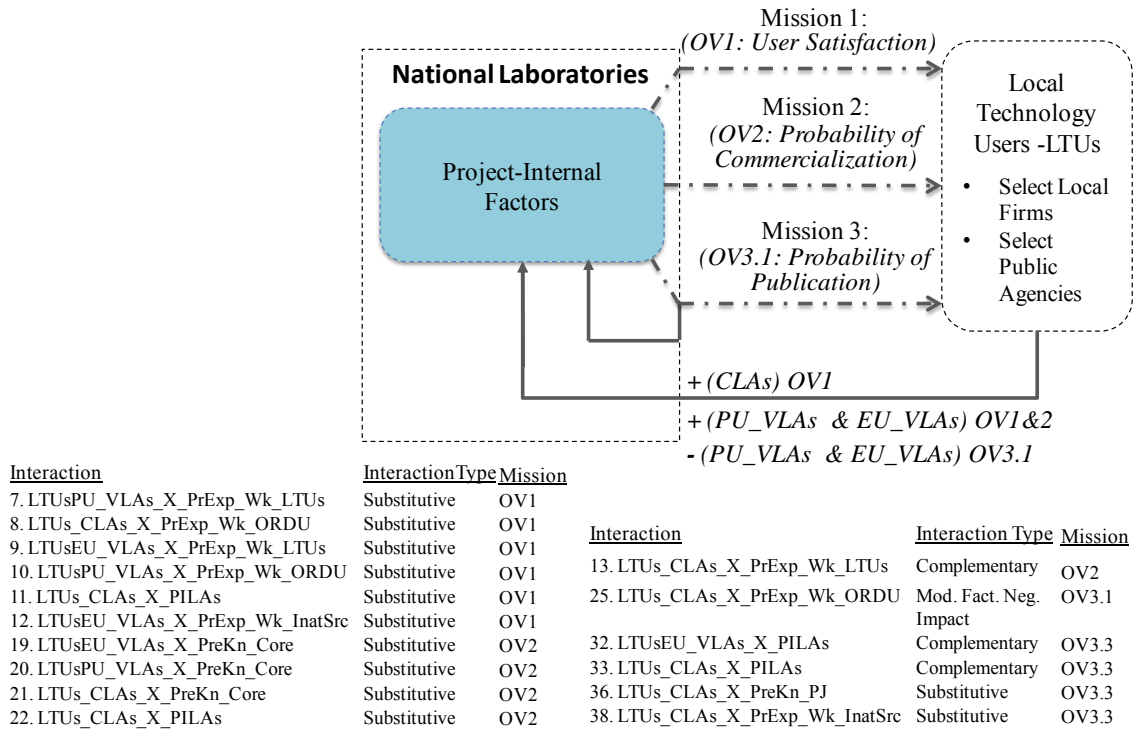
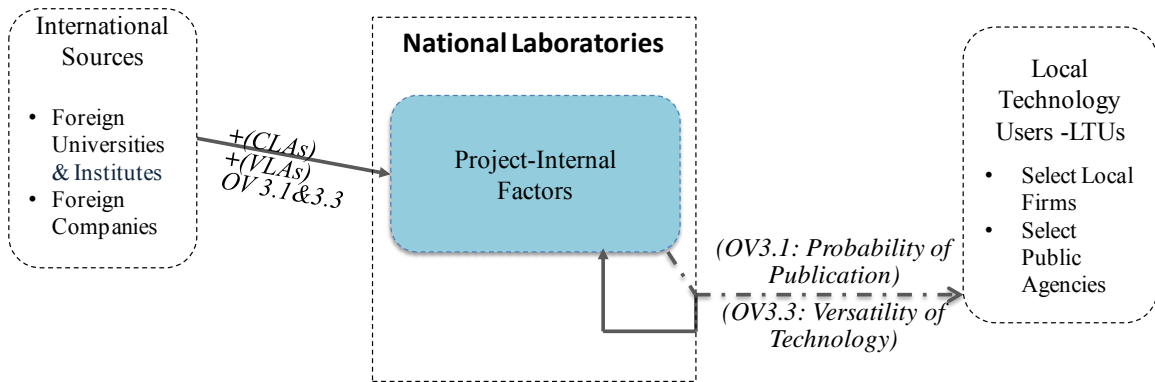


Figure 6.8: The knowledge management subsystem of the National Laboratory Knowledge Management System that pertains to knowledge inflows from local technology users

Figure 6.8 depicts the knowledge subsystem of the national laboratory system that pertains to knowledge inflows from local technology users. It is derived from the results of testing hypotheses 3a, 3b and 3c, as well as from the output of the interaction model in section 5.5. Figure 6.8 has much in common with figure 3.4, and a comparison between the two figures only reveals one distinct difference—the impact of vicarious learning with local technology users on the probability of publication is negative. In spite of this discrepancy, the existence of a subsystem of the national laboratories system that governs

knowledge inflows from local technology users has been verified, and the model from figure 3.4 has been validated to a significant degree.

6.6.1.4 Conclusions Pertaining to Knowledge Inflows from International Sources



<u>Interaction</u>	<u>Interaction Type</u>	<u>Mission</u>	<u>Interaction</u>	<u>Interaction Type</u>	<u>Mission</u>
4. InatSrc_VLAs_X_PreKn_Core	Input Factor	OV1	26. InatSrc_VLAs_X_PreKn_Core	Complementary	OV3.1
	Neg. Impact		31. InatSrc_VLAs_X_PILAs	Substitutive	OV3.1
15. InatSrc_CLAs_X_PreKn_Core	Complementary	OV2	37. InatSrc_CLAs_X_PILAs	Substitutive	OV3.3
23. InatSrc_VLAs_X_PreKn_Core	Substitutive	OV2			
24. InatSrc_VLAs_X_PILAs	Substitutive	OV2			

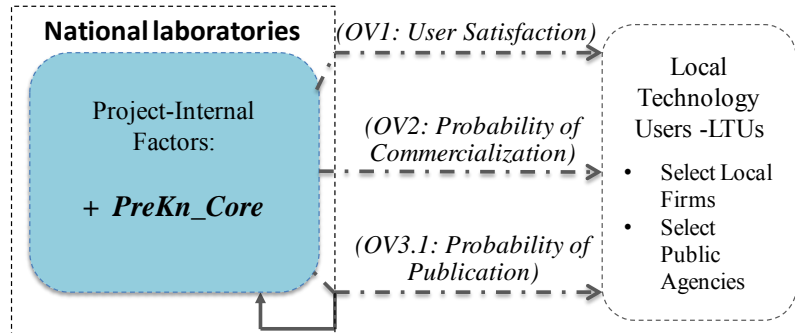
Figure 6.9: The knowledge management subsystem of the National Laboratory Knowledge Management System that pertains to knowledge inflows from international sources

Figure 6.9 depicts the knowledge subsystem of the national laboratory system that pertains to knowledge inflows from international sources. It is derived from the results of testing hypotheses 4a, 4b and 4c, as well as from the output of the interaction model in section 5.5. Figure 6.9 has much in common with figure 3.5, and a comparison between the two figures only reveals one distinct difference—external learning with local with international sources has no direct, statistically significant impact on user satisfaction and the probability of commercializing a technology. Only the interaction between contextual

learning about international sources and prior knowledge of the core technology has a statistically significant impact on the probability of commercializing a technology (see interaction no. 15). In spite of this discrepancy, the existence of a subsystem of the national laboratories system that governs knowledge inflows from local technology users has been verified, and the model from figure 3.3 has been validated to a significant degree.

6.6.2 Prior Knowledge about the Core Technology

The approach identifying knowledge subsystems from section 6.6.1 can also be used to draw specific conclusions about internal sources of knowledge, which, as shown in section 5.4, can have direct impact on performance. It may therefore be possible demonstrate the existence of knowledge subsystems that govern project-internal knowledge. However, the research described in this dissertation concerns itself primarily with knowledge inflows; project internal knowledge is mostly viewed as a way to enhance the capacity to absorb knowledge from external sources. Therefore characterizing the structure of knowledge subsystems for project-internal knowledge goes beyond the scope of this dissertation.



<u>Interaction</u>	<u>Interaction Type</u>	<u>Mission</u>	<u>Interaction</u>	<u>Interaction Type</u>	<u>Mission</u>
2. LocUniv_VLAs_X_PreKn_Core	Complementary	OV1	19. LTUsEU_VLAs_X_PreKn_Core	Substitutive	OV2
3. InatSrc_VLAs_X_PreKn_Core	Input Factor	OV1	20. LTUsPU_VLAs_X_PreKn_Core	Substitutive	OV2
	Neg. Impact		21. LTUs_CLAs_X_PreKn_Core	Substitutive	OV2
14. ORDU_VLAs_X_PreKn_Core	Input Factor	OV2	23. InatSrc_VLAs_X_PreKn_Core	Substitutive	OV2
	Neg. Impact		26. InatSrc_VLAs_X_PreKn_Core	Complementary	OV3.1
15. InatSrc_CLAs_X_PreKn_Core	Complementary	OV2			

Figure 6.10: The knowledge management subsystem of the National Laboratory Knowledge Management System that pertains to prior knowledge about the core technology

There is one exception to this rule—prior knowledge about the core technology. A proposal for a knowledge subsystem that governs prior knowledge about the core technology is illustrated in figure 6.10. This form of knowledge has been shown to have a statistically significant positive impact on user satisfaction, the probability of commercialization and the probability of publication in the integrated regression models of these performance metrics, even though the last of these three performance metrics is misaligned with the first two.

Prior knowledge about the core technology has a negative complementary interaction with vicarious learning with other R&D project groups within the national laboratories, at

least when it comes to the probability of commercialization (see interaction no. 14). When the level of prior knowledge about the core technology is low, then the probability of commercialization decreases very rapidly over the domain of vicarious learning with ORDUs. By contrast, if the level of knowledge of about the core technology is high, then the impact of vicarious learning with ORDUs on the probability of commercialization is negligible. It is thus in the national laboratories' interest to keep a high degree of knowledge about the core technology within the project groups so that the negative impact of vicarious learning with ORDUs is minimized for future projects.

Interviews with project managers suggest that the top management of the national laboratories is aware of the issue of inter-departmental barriers to knowledge, even though it does not know about the result of the study in this dissertation. The senior managers of the national laboratories would like to break down the barriers to knowledge flow between the various project groups within the national laboratories, and they also understand the potentially exceptional role that prior knowledge about the core technology could play in that context.

The management of the national laboratories is considering creating a special position called 'chief executive engineer' for every project. The chief executive engineer is supposed to be a person with a high degree of knowledge about the core technology of a project. His/her role will be to act as an intermediary between project groups. An overwhelming majority of project managers who commented on the position of chief executive engineer did so favorably, but they insisted that the chief executive engineer should have expertise in the core technology upon which the project depends. The

project managers also suggested that the idea of a chief executive engineer has lots of support within NSTDA.

The results of my study show that having a chief executive engineer with a high degree of knowledge of the core technology under development in every project group could make the national laboratories significantly more ambidextrous. Vicarious learning with other R&D project groups already enhances the exploratory component by increasing the probability of generating a publication. If the chief executive engineers can use their knowledge about the core technologies of their respective projects to mitigate the negative impact that vicarious learning with other R&D project groups has on the probability of commercialization of a technology, then they will enhance the exploitative component of the projects as well.

6.6.3 The Relative Importance of Internal and External Learning

Section 4.7.4 described the hierarchical approach to regression that was used to benchmark the explanatory and predictive power of five regression models for each output variable (see figure 4.2). The intent of this endeavor was to compare the impact of external learning, project-internal learning activities (PILAs), prior experiences, and prior knowledge on performance of R&D projects. The results of this benchmarking effort, which are described in section 5.3.1, have led to a series of conclusions about the relative impact of internal and external knowledge.

Conclusion 6.6.3-1: Regardless of mission, knowledge inflows from outside the project group impact the performance of R&D projects more significantly than knowledge from inside the project group does.

Conclusion 6.6.3-2: Regardless of mission, knowledge inflows from outside the national laboratories impact the performance of R&D projects more significantly than knowledge from inside the R&D project group does. The impact of knowledge inflows from inside the national laboratories (other R&D project groups) on the performance of a project is comparatively minor.

Conclusion 6.6.3-3: Utilizing both internal and external sources of knowledge increases the impact on performance dramatically.

According to interviews with project managers, most R&D projects within the national laboratories cannot be completed solely on the basis of knowledge that is available in the project group that delivers the technology. Especially, delivering advanced technology requires advanced technological knowledge that is unavailable in the project group. Project managers tend to supervise research that is within their own area of technical expertise, so engaging with other R&D units within the national laboratories should, in principle, be fruitful. However, in practice this does not turn out to be the case because project groups tend to work on projects that are highly specialized and not relevant to other projects. In addition, project groups within the national laboratories compete with each other for resources. Some project managers even claimed that they are not inclined to reveal secrets about their technology to other project groups. However, most of the

advanced knowledge that is required to deliver advanced technology resides outside of the national laboratories. Therefore, the project group needs to acquire complementary knowledge outside the national laboratories. The synergy between internal and external knowledge improves performance. This state of affairs calls for a program for Open Innovation at the national laboratories, which is currently in the planning stage at NSTDA.

7. SUMMARY, CONTRIBUTIONS AND LIMITATIONS

In this chapter, I summarize my research. I restate the research questions and report on how they have been addressed by the findings of my research. I also examine the theoretical and practical implications of the findings from my study. I discuss how this dissertation has contributed to academic research in various sub-fields of technology management and in other, related fields of study. In addition, I show how findings from this dissertation have revealed management practices that are particularly useful for national research laboratories in technological latecomer countries. I also discuss how findings from this dissertation may have implications for national policy in Thailand and other latecomer countries, yet I make the argument that the findings of my study can be generalized beyond technological latecomer countries and beyond the national laboratories setting, if proper follow-on studies are conducted. Finally, I identify some of my study's limitations, and I suggest how they can be overcome through further research using methods that I have in part developed in this dissertation.

7.1 RESTATING THE RESEARCH GAPS AND THE RESEARCH QUESTIONS

At the end of chapter 2, I identified a series of gaps in the academic literature that gave rise to the research questions that I have addressed in my dissertation. Most importantly, I discovered that *no quantitative study on the impact of the four main sources of external knowledge* (other R&D project groups within the national laboratories; local universities; local technology users and international sources) *and of the three main sources of internal knowledge* (prior knowledge, prior experience, project-internal learning

activities) *on the performance of NLs in TLCs had ever been done*. This primary research gap gave rise to the primary research question of my dissertation – *to what degree does engagement with the external sources of knowledge affect the performance of national laboratories in technological latecomer countries?*

In section 2.6, I broke down this overarching research question into four specific research questions.

- **Research Question RQ-1** – *What is the **relative** impact on the performance of national laboratories in latecomer countries of engaging a) with other project groups within the same organization; b) with the sources of foreign knowledge; c) with sources of user knowledge and d) with other sources of domestic knowledge?*
- **Research Question RQ-2** – *What is the effect of a project group’s **prior knowledge** on the relationship between the project group’s degree of engagement with external sources of knowledge and the project’s performance?*
- **Research Question RQ-3** – *What is the effect of a project group’s **prior experience** on the relationship between the project group’s degree of engagement with external sources of knowledge and the project’s performance?*
- **Research Question RQ-4** – *What is the effect of a project group’s **internal learning capability** on the relationship between the project group’s degree of engagement with external sources of knowledge and the project’s performance?*

Hypotheses 1 through 4 were set up to address RQ-1 for the three basic missions of the national laboratories. Hypotheses 5, 6 and 7 were respectively set up to address RQ-2,

RQ-3 and RQ-4. The results show all of the seven proposed hypotheses were statistically significant, under a variety of circumstances. The relative impact of the various knowledge inflows on four performance criteria (OV1, OV2, OV3.1 and OV3.3) has been discussed in section 5.4.5. The results that pertain to research questions RQ-2, RQ-3 and RQ-4 have been presented in section 5.5. I consequently argue that the primary research gap from section 2.6 has been closed, and its associated research questions have been answered. I consider this the primary contribution of my dissertation research.

However, as I have noted repeatedly in chapter 5, the results of my research are much more nuanced and differentiated than I had originally anticipated. Hypotheses 1 through 7 have been confirmed under special circumstances and I have been able to identify what these circumstances are (see Figures 6.2 through 6.10). I consider this a significant contribution of my research as well. Finally, the nuanced and differentiated results enable me to make additional, initially unforeseen contributions to academic theory, management practice and research methods, which are discussed in the following sections.

7.2 ACADEMIC CONTRIBUTIONS

The contributions of the empirical study in this dissertation span a variety of research streams within the field of technology management including R&D management, technology transfer and new product development. This dissertation also contributes to the fields of organizational learning and the study of absorptive capacity by providing a

more detailed understanding about how external sources of knowledge affect the performance of research and development projects within national laboratories.

7.2.1 R&D Management

The findings of this dissertation present an academic contribution to the literature on R&D management, and the study of R&D management is one of the central aspects of technology management. Of late, two research streams have been increasing in importance in the R&D management literature: Open Innovation and organizational ambidexterity. My dissertation research speaks to both streams of literature.

7.2.1.1 R&D Management and Open Innovation

Organizations, in particular high-tech firms, have opened their boundaries to external knowledge and tried to identify strategies to access knowledge resources externally (Chesbrough, 2003; Chesbrough *et al.*, 2006; Gassmann, 2006). This phenomenon was initially explored in studies that are described in the literature on Open Innovation (Chesbrough, 2003; Chesbrough *et al.*, 2006; Gassmann, 2006). The principles that were identified in these studies have also been shown to apply to more traditional and mature industries (Chesbrough & Crowther, 2006), but have never been demonstrated in public organizations. Yet, like many firms in private industry, the national laboratories in technology latecomer countries link up and interact with external entities to initiate, import, modify or diffuse new technologies (Freeman, 1992, Mazzoleni & Nelson, 2007, Intarakumnerd *et al.*, 2002).

This dissertation makes an academic contribution in refining a framework of how national laboratories link and interact with external entities (see Figure 6.1). This framework enhances the understanding of how the Open Innovation approach is practiced in national laboratories. This dissertation also develops a benchmarking method to quantify quantitative data to confirm the impacts of engaging with external sources of knowledge on the performance of national laboratories (see section 5.3). Thus, this dissertation provides both framework and quantitative data to confirm that the principle of Open Innovation applies to the NLs of TLC.

7.2.1.2 Identifying the Ambidexterity Challenge in the National Laboratories

My dissertation has shown that the national laboratories face a significant ambidexterity challenge (section 6.5), just like private corporations do (Tushman & O'Reilly, 1996; O'Reilly & Tushman, 2004; Gibson & Birkinshaw, 2004; Raisch & Birkinshaw, 2008; O'Reilly & Tushman, 2008; Ambos *et al.*, 2008; Simsek, 2009; Raisch *et al.*, 2009; Andriopoulos & Lewis, 2009; Taylor & Helfat, 2009; Rothaermel & Alexandre, 2009; Cao *et al.*, 2009; Jansen *et al.*, 2009; Mom *et al.*, 2009; O'Reilly & Tushman, 2011). Mission 1 (user satisfaction) and mission 2 (commercialization of technology), which are clearly exploitative, are not well aligned with mission 3 (generating and R&D capability for the country), which enables exploratory activities. Further research should determine whether practices that have enhanced organizational ambidexterity (e.g., d'Arbeloff, 1996; Simsek, 2009; Carmeli & Halevi, 2009) in private industry also apply to public institutions like the national laboratories (Y.-C. Chang *et al.*, 2009).

7.2.2 Technology Transfer

In the technology transfer literature, the NLs are considered as a source of technology for private industry (W. M. Cohen *et al.*, 2002). Therefore, the direction of knowledge flow discussed in technology transfer literature tends to focus on how knowledge flows out of the national laboratories and in to industries. However, in technological latecomer countries both the NLs and private industrial firms are likely to have insufficient resources to research and develop their technology internally. They NLs rely on knowledge from external sources, both foreign and domestic, just like their counterparts in private industry rely on the NLs for technology. Yet, the relationship between knowledge flows into the NLs and knowledge transfer out of the NLs is not well understood, primarily because very few academic studies of this topic have been performed. This dissertation has enhanced our understanding of how knowledge that flows into the NLs in TLCs impacts technology transfer out of the NLs (Figures 6.2 through 6.4). It consequently contributes to closing this gap in the academic literature.

7.2.3 New Product Development

This study has increased our understanding about how NLs enable or participate in new product and new service development (NPSD) process. In NPSD literature, the outflow of knowledge from NLs links to the NPSD process at various stages (R. G. Cooper & Kleinschmidt, 1986; R. G. Cooper, 1994; Ulrich & Eppinger, 1995; H. Kim & Park, 2010). Also, user requirements and user feedback may flow back into the labs to help the NLs develop technology that is suitable for current and future demands by technology

users (Gregersen, 1992). The findings of the empirical study in this dissertation, which has investigated the impact of knowledge inflows on the performance of the NLTs, has been able to provide significant insight into how private firms can leverage NLTs more effectively in their NPSD process.

It is well known that user engagement can lead to supplier innovations that tend to occur along dimensions of merit (von Hippel, 1988). I have shown that this is also true when the national laboratories are the supplier of technology and the local technology users develop the product. In addition, I have provided a theoretical framework that consists of a toolkit of micro-levers, which helps the laboratory managers them satisfy user needs pertaining to new product development or commercialize technology for new product development more effectively (figures 6.2 and 6.3).

7.2.4 Organization Learning and Absorptive Capacity

The study in this dissertation has been able to contribute to the field of organizational learning by enhancing our understanding of how engagement with external sources of knowledge impacts the performance of national laboratories in technology latecomer countries and perhaps elsewhere. For example, I have been able to build on the work of Bresman, 2010, by identifying a set of circumstances under which contextual learning has a greater impact on performance and another set of circumstances under which vicarious learning has a greater impact on performance. Furthermore, according to Argote and Miron-Spektor, 2011 (p. 1123), “organizational experience interacts with the context to create knowledge.” My research has validated this principle for the national laboratories

in technology latecomer countries, and I have identified the factors that determine the impact that knowledge creation has on organizational performance.

This dissertation may also be able to make contributions to the knowledge management literature. For example, a part of validating the overarching framework for knowledge flows in the national laboratory system (section 2.5) was the identification of knowledge subsystems within the national laboratory system, first by literature search (chapter 3) and subsequently by analysis of quantitative and qualitative data. Some of the subsystems that have been identified are mission specific (section 6.4); others are phenomena specific (section 6.6). These subsystems should in principle be easier to manage than the national laboratories system as a whole. However, they need to be characterized in further detail before they can be used as a framework for management practice.

The findings of the study in this dissertation have established that managing a diverse set of knowledge sources requires managers to differentiate between various kinds of absorptive capacity. In fact, the nature of absorptive capacity is highly selective. This discovery is perhaps the most important contribution of my dissertation research. The conclusion that is associated with this discovery has been stated in section 6.3: “... *the capacity of R&D project groups within the national laboratories to absorb knowledge from external sources is not just related to prior related knowledge; it is also a function of the source of external knowledge, the knowledge pathway into the project group; the source of complementary or substitutive knowledge that resides within the project group; and the mission to which the knowledge contributes.*” I believe this discovery warrants

further academic study so that the plethora of absorption mechanisms that have been identified in this dissertation can be characterized for use by practitioners.

7.3 CONTRIBUTIONS TO MANAGEMENT PRACTICE

Understanding the impact of engagement with external sources of knowledge on performance of research projects can help managers of research and development projects at national laboratories in technological latecomer countries design their strategy for engaging with external entities more effectively. Best practices for engaging with external entities, which allow managers at NLs in TLCs to learn about how to manage knowledge inflows, have been identified in this dissertation. The process of learning consists of deciding which external source of knowledge to tap, and identifying the best pathways for knowledge inflow into the national laboratories and the various project groups that actually work on R&D projects (see Figures 6.6 through 6.10, knowledge subsystems of the National Laboratories Knowledge Management System). My dissertation has also provided practical insights into how the performance of R&D projects is impacted when knowledge that has flowed in from external sources is combined with knowledge that is either already present within the group or evolving currently through internal learning processes (see Figures 6.2 through 6.5, knowledge subsystems of the National Laboratories Knowledge Management System that are mission specific).

These insights enhance the ability of project managers to manage absorptive capacity within their groups. Once again, the toolkit of micro-levers that my dissertation provides needs to be mentioned (figures 6.2 through 6.10). It indicates into which sources of external knowledge the project group should tap, and which internal source knowledge to encourage so that the inflow from the external source of knowledge can be absorbed. Finally, it should be noted that interviews with project managers and project evaluators have revealed an approach for ameliorating the ambidexterity challenge—the creation of the position of ‘chief executive engineer’ within each R&D project group (section 6.6.2).

7.4 IMPLICATIONS FOR NATIONAL POLICY

The study in this dissertation has investigated how the national laboratories in technological latecomer countries interact with their national innovation systems. Any significant findings of the study in this dissertation could consequently have implications for national policy. Based on the findings of this study, policymakers in a technological latecomer country may be able to make structural adjustments to the national laboratories or to some of the domestic entities with which they interact. These adjustments could potentially enhance and accelerate social and economic development of their nation. For example, NSTDA is currently launching an Open Innovation policy for the national laboratories to which the findings of this dissertation could in principle contribute. It is also not inconceivable that the findings of this study could induce modifications to

foreign policy that increase the national absorptive capability by making the knowledge inflow from abroad more efficient and effective.

7.5 LIMITATIONS

The purpose of the research in this dissertation is to identify and determine the relative importance of the factors that contribute to the success of R&D projects within the national laboratories of technology latecomer countries. I test the impact on project performance of changes in the values of various input variables, moderating variables and control variables. In essence, I have conducted variance research (Mohr, 1982), which treats the national laboratories as a black box, rather than process research, which looks inside the black box (Zenobia & Weber, 2012).³⁰

The following limitations of my research are a consequence of its quantitative nature. Firstly, this study uses item scales to capture the complex behavior of R&D project groups as they engage with external sources of knowledge. Research that uses item scales is designed to elicit information that has been mentioned in the existing literature. It may not capture some aspects of the behavior of the respondents that the research

³⁰ “Process research is a style of inquiry that seeks to discover causal relationships and patterns in the sequence of events over time; it has often been used to study technology adoption (Downs & Mohr, 1976; A. Langley & Truax, 1994; Rogers, 2003; Van de Ven & Huber, 1990). Mohr, 1982, contrasted process research with what he termed ‘variance’ research, the more familiar style of inquiry that seeks to determine covariance and correlation among variables, independent of their time order. Process research aims to construct theories that explain the time order of events; it does not strongly emphasize relationships among variables influencing the rate or outcome of these events (Mohr, 1982; Abbott, 1990). Process research is less structured and more qualitative in character than variance research. Some of the methods that have been used for process research include case studies, grounded theory, and sequence analysis (A Langley, 1999), and these methods have occasionally been applied in combination e.g., Leonard-Barton, 1990.” (Zenobia & Weber, 2012, p. 5)

design does not anticipate. For example, the quality of engagement to external sources of knowledge is not directly measured in this study. A particular project group may engage with the external sources of knowledge very frequently, but the quality of knowledge inflows may be lower than that of another project group, which does not engage with the external sources very often. Secondly, this study uses a retrospective approach to collect data from R&D project managers and project evaluators. This approach may cause bias and error in research results. However, using data from R&D projects that have been completed in the past two years has minimized the bias and error resulting from data collection. Thirdly, the sample size of R&D projects in this study may be not enough to capture with statistical significance the impact of all factors pertaining to absorptive capacity, which may complement or substitute the inflow of knowledge from external sources. Even though 39 statistically significant interactions between input factors and moderating factors have been identified, the interaction matrices in table 5.20 look rather sparse. A larger sample size may be required to characterize the influence of additional interactions.

Another limitation of my dissertation research results directly from its hierarchical approach to multiple regression (section 4.7.4 and figure 4.2 of my dissertation; Aiken & West, 1991; J. Cohen *et al.*, 2003, Espinosa *et al.*, 2007). The premise of my research was that knowledge from various internal sources could enhance or diminish the capacity to absorb knowledge that flows in from external sources. Variables associated with knowledge inflows were consequently treated as input variables, and variables associated with internal knowledge were treated as moderating variables (see figure 4.1). Factor

analysis minimized multi-collinearity and identified the input factors and moderating factors that respectively represented knowledge inflows and internal knowledge. I subsequently looked at the relative importance of knowledge from external sources and internal sources, by comparing the explanatory power of the knowledge inflow baseline model, the project group baseline model and the intra-organization baseline models (section 5.3). Hypotheses 1 through 7 were also tested by multiple regression analysis. The integrated model tested hypotheses 1 through 4 (section 5.4); the interaction model was used to test hypotheses 5 through 7 (section 5.5). I did not move to the next step of generating a structural equation model, which would have covered all interactions between all factors, because that step would have exceeded the scope of my dissertation research as originally proposed..

The survey portion of my research was constrained by the limitations of variance research. This approach did not let me provide a detailed characterization of the internal processes that govern R&D within the national laboratories in Thailand. However, I was able to interview 123 project managers within NSTDA at the time I administered the survey to them. I was able to extract qualitative information from these interviews, which let me peek inside the black box of organizational learning in the national laboratories. Combining the insights gained from these interviews with the quantitative results from the survey enabled me to come to the conclusions that were presented in chapter 6.

Unfortunately, for reasons of confidentiality, I was not able to record the interviews on audio, which prevented me from coding them, and going through the formal, inductive theory-building exercises that are associated with process research (e.g., Yin, 2008;

Eisenhardt, 1989; Strauss & Corbin, 1998; Miles & Huberman, 1994). Thus, I recommend qualitative follow-on research to my dissertation, perhaps sequence analysis (Abbott, 1990; Miles & Huberman, 1994; A Langley, 1999), to gain an in depth understanding of the internal mechanisms of research and development within the NSTDA. It may also be useful to conduct case study research (Yin, 2008) at NSTDA. Each knowledge subsystem would constitute a case, and the inner mechanisms of knowledge management within the national laboratories would be revealed by comparing and contrasting cases (Miles & Huberman, 1994). Once these mechanisms have been identified and characterized, I recommend running a structural equation model on the data that I have collected with my questionnaire, so that the constructs that emerge from the case studies can be validated in a quantitative sense.

Another limitation of this dissertation pertains to generalizing its results beyond technology latecomer countries. According to Intarakumnerd *et al.*, 2002 (in section 4.2), organizations in technological latecomer countries tend to possess very limited capabilities to facilitate and produce intensive technological learning. They tend to have lower capacity in absorbing knowledge inflows from external sources than organizations in developed countries. Therefore, the influence of knowledge inflows on organizational performance may be different in these countries. To generalize the theoretical framework beyond organizations in latecomer countries, additional research on the national laboratories in other countries may be required. Nonetheless, many of the recommendations and best practices that may emerge from my dissertation could be

applicable in many countries, including countries that are not latecomers to advanced technological development.

It should be noted that important sources of external knowledge such as competitors, suppliers, regulations, other industries, consultants, consortia, start-ups and communities (e.g. McAdam *et al.*, 2006; Laursen & Salter, 2006; Ili *et al.*, 2010) are not included in the scope of this study. My dissertation has focused on the four critical sources of external knowledge for R&D projects in national laboratories of technological latecomer countries. To generalize the framework of this dissertation beyond the national laboratories in technology latecomer countries, additional studies, which identify and compare the critical sources of external knowledge for national laboratories in latecomer countries to those of other countries, need to be done. Furthermore, the results of my study need to be compared to the results of studies that have been or will be conducted in settings other than the national laboratories (e.g., universities, research labs in private industry), in order to test whether the findings of this study also apply in other settings.

7.6 METHODS CONTRIBUTION

I would like to point out that my dissertation contains a vehicle for conducting much of the follow-on research that has been suggested above. I believe that the questionnaire that has been developed addresses issues that are common to many R&D contexts; it can consequently be used as a benchmarking tool for knowledge flow and its impact on performance. The same approach to data analysis that was used in this dissertation could also be used to study other settings.

Repeating the study that I have conducted for my dissertation at many settings is likely to generate insight into how knowledge flow impacts R&D management in general. One could compare the various approaches to managing knowledge in the national laboratories of various latecomer countries (e.g. NSTDA versus TUSSIDE in Turkey), or the approaches that are used by national laboratories in countries that are at different stages of economic development (e.g. NSTDA versus KIST in Korea and the Fraunhofer-Gesellschaft in Germany). Significant insight into managing knowledge within R&D organizations may also be gained by comparing the approaches of national laboratories to corporate laboratories (e.g., the Fraunhofer-Gesellschaft versus IBM's Watson Laboratories).

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APPENDICES

APPENDIX A: 17 PATHWAYS TO FACILITATE KNOWLEDGE TRANSFER FROM TECHNOLOGY PRODUCERS TO LTUs

Pathways	Author (s)
Licensing*	Rogers <i>et al.</i> , 2001; Petroni & Verbano, 2000; King & Nowack, 2003; Feller <i>et al.</i> , 2002; Agrawal, 2002; Feldman <i>et al.</i> , 2002; Shane, 2002; Chapple <i>et al.</i> , 2005; J. Lee & Win, 2004; Siegel, 2004; Bercovitz, 2006; del Campo <i>et al.</i> , 1999
Cooperative R&D*	Rogers <i>et al.</i> , 2001; Carayannis & Gover, 2002; Agrawal, 2002; del Campo <i>et al.</i> , 1999; Guan <i>et al.</i> , 2006; Liu & Jiang, 2001
Contract research*	J. Lee & Win, 2004
Joint research*	Zucker <i>et al.</i> , 2002; Kulve & Smit, 2003; J. Lee & Win, 2004; Liu & Jiang, 2001
Consulting*	Agrawal, 2002; Guan <i>et al.</i> , 2006
Seminars and conferences*	Agrawal, 2002; J. Lee & Win, 2004
Training*	Hong, 1994; Guan <i>et al.</i> , 2006
Direct selling*	J. Lee & Win, 2004
Tech & business incubator*	Phillips, 2002; Lofsten & Lindelof, 2003; Markman <i>et al.</i> , 2005
Tech & science park and R&D facility*	Lofsten & Lindelof, 2003; Petroni & Verbano, 2000; Markman <i>et al.</i> , 2005; Liu & Jiang, 2001; Feller <i>et al.</i> , 2002
Spin off	Rogers <i>et al.</i> , 2001; Sedaitis, 2000; Bercovitz, 2006; del Campo <i>et al.</i> , 1999; J. Lee & Win, 2004
Publications	Rogers <i>et al.</i> , 2001; Agrawal, 2002; Decter, 2007
Patents	Agrawal, 2002; Decter, 2007
Prototyping	Feller <i>et al.</i> , 2002
Tech& Industry consortia	Bessant, 1999; Hemphill, 2006; J. Lee & Win, 2004
Meeting and knowledge exchange	Rogers <i>et al.</i> , 2001; Feller <i>et al.</i> , 2002; Agrawal, 2002
Vertical Partners	del Campo <i>et al.</i> , 1999

Asterisks ‘*’ refer to 10 channels for external technology commercialization of NLTs

APPENDIX B: QUESTIONNAIRE FOR PROJECT MANAGERS (POST-VALIDATION)

This questionnaire is a part of a doctoral research in Engineering and Technology Management at Portland State University. The research investigates the impact of knowledge inflows into a project on research and development organizations. We ask you to participate in your role as a **project manager** in such an organization. Your responses will help us to better understand how knowledge inflows affect research and development organizations.

B.1 General information interviewed by Patravadee: Total 10 questions.

Project titleProject ID

Project managerTel

QUESTIONS	ANSWERS
<p>1. R&D strategy:</p> <p>Based on the OECD’s taxonomy of R&D activity (OECD, 1981, pp. 53-55), I classify the maturity of a research and development project as follows:</p> <p>a. A project is in the basic research stage if it consists of “experimental or theoretical work undertaken primarily to acquire new knowledge of the underlying foundations of phenomena and observable facts, without any particular application or use in view” (OECD, 1981, p. 54).</p> <p>b. A project in the applied research stage is “also [an] original investigation undertaken in order to acquire new knowledge. It is however, directed primarily towards a specific practical aim or objective” (OECD, 1981, p. 54).</p> <p>c. A project is in the development and demonstration stage, if it consists of “systematic work,..., which is directed to producing new materials, products, and devices, to installing new processes, systems, and services, and to improving substantially those already produced or installed” (OECD, 1981, p. 55).</p> <p>Please classify the project by stage of technological development by using the definitions from below.</p>	<p>a. Basic Research b. Applied Research c. Development and Demonstration d. Other (please identify).....</p>
<p>2. Please classify the project by technology type.</p>	<p>a. Biotechnology b. Materials technology c. Electronics & computer technology d. Software technology e. Nanotechnology</p>

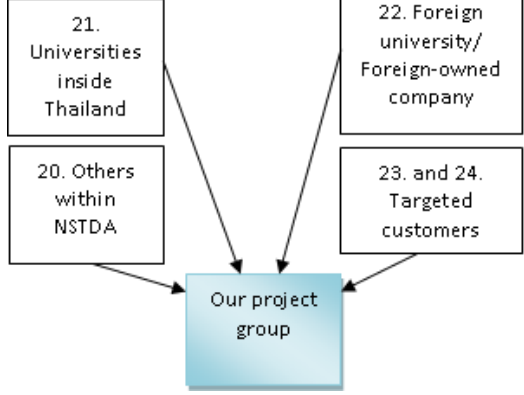
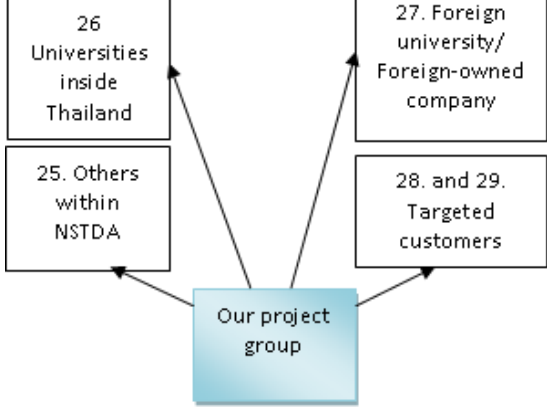
QUESTIONS	ANSWERS
	f. Other (please identify).....
3. Please identify as many strategic programs of NSTDA as possible, to which the output of this project can be applied.	a. The Rice Program b. The Tapioca Program c. The Rubber Program d. The Seed Program e. The Plants for the Future Program f. The Animal Production and Animal Health Program g. The Food Innovation Program <hr/> h. The Newly Emerging Disease - Re-emerging Disease Program i. Preventive, predictive and personalized medicine j. Healthcare practice and medical devices k. The Genotype Technology Program l. Assistive Devices and Technologies for People with Disabilities and The Elderly Program <hr/> m. The Sustainable Environment Program n. The Resource and Energy Efficiency Program o. The Renewable Energy and New Technology Research Program p. The Technology for Rural Development Program q. The Bio-resources Program <hr/> r. The Hard Disk Drive Industry Research Program s. The Air-conditioning and Refrigerator Industry Program t. The Automotive and Automotive Parts Industry Program

QUESTIONS	ANSWERS
	u. Digital engineering v. Sensor and intelligent system w. Functional materials x. Service research and innovation y. Other (please identify)
Project members 4. Number of full-time members working on this project 5. with Ph.D. as the highest degree 6. with Masters as the highest degree	Total people people people
Prior knowledge (before the start of this project): 7. How long was your group developing technology that is directly relevant or useful to this project?	a. Never b. < 1 year c. 1 to <3 years d. 3 to <5 years e. 5 to <7 years f. >7 years
8. How many journal publications that were directly relevant or useful to this project did your project group generate before this project began?	a. Never b. 1 issue c. 2 issues d. 3 issues e. 4 issues f. > 4 issues
9. How many conference proceedings that were directly relevant or useful to this project did your project group generate before this project began?	a. Never b. 1 issue c. 2 issues d. 3 issues e. 4 issues f. > 4 issues
10. How many patents that were directly relevant or useful to this project did your project group generate before this project began?	a. Never b. 1 issue c. 2 issues d. 3 issues e. 4 issues f. > 4 issues

B.2 Activities pertaining to obtaining knowledge of this project: Total 29 questions

The answers to the following questions will be measured by using psychometric scales, Likert scales, ranging from 1 to 6. Please state your opinions by answering the following questions.

Questions	Almost never (1)	Very rarely (2)	On occasion (3)	Some what frequently (4)	Very frequently (5)	Almost always (6)
11. At least some members of our project group looked for technical ideas in internal reports inside NSTDA.						
12. At least some members of our project group looked for technical ideas in papers, reports and websites published by universities inside Thailand.						
13. At least some members of our project group looked for technical ideas in papers, reports and websites that were published by foreign universities and foreign-owned companies.						
14. To understand the needs of our targeted customers , at least some members of our project group looked for technical requirements in industry newsletters, bulletins, websites and trade journals.						
15. At least some members of our project group looked for data on what other teams inside NSTDA were doing on similar or complementary projects.						
16. At least some members of our project group looked for data on what other teams at universities inside Thailand were doing on similar or complementary projects.						
17. At least some members of our project group looked for data on what other teams at foreign universities and foreign-owned companies were doing on similar or complementary projects.						
18. At least some members of our project group looked for data on what our targeted customers were doing on similar or complementary projects.						

Questions	Dis-agree strongly (1)	Dis-agree (2)	Tend to dis-agree (3)	Tend to agree (4)	Agree (5)	Agree strongly (6)
<p>19. Experts within NSTDA talked to our project group about the lessons learned from <u>their</u> past experiences.</p> <p>20. Experts from universities inside Thailand talked to our project group about the lessons learned from <u>their</u> past experiences.</p> <p>21. Experts from foreign universities and foreign-owned companies talked to our project group about the lessons learned from <u>their</u> past experiences</p> <p>22. Our targeted customers who have production units talked to our project group about how to develop technology that is suitable for <u>their</u> requirements.</p> <p>23. Our targeted customers who are end users talked to our project group about how to develop technology that is suitable for <u>their</u> requirements.</p>						
<p>24. At least some members of our project group talked to experts within NSTDA about lessons learned from <u>our</u> past experiences.</p> <p>25. At least some members of our project group talked to experts within universities inside Thailand about lessons learned from <u>our</u> past experiences.</p> <p>26. At least some members of our project group talked to experts from foreign universities and foreign-owned companies about lessons learned from <u>our</u> past experiences.</p> <p>27. At least some members of our project group talked to our targeted customers who have production units to determine ways to improve <u>our</u> project.</p> <p>28. At least some members of our project group talked to our targeted customers who are end users to determine ways to improve <u>our</u> project.</p>						

Questions	Dis-agree strongly (1)	Dis-agree (2)	Tend to dis-agree (3)	Tend to agree (4)	Agree (5)	Agree strongly (6)
29. Our project group took time to <u>figure out</u> ways to improve our work process.						
30. Our project group took time to <u>monitor</u> our project's work progress.						
31. Individuals within our project group <u>spoke up</u> to challenge technical assumptions concerning issues that were under discussion among members of our project group.						
32. The project group <u>implemented</u> suggestions made by team members.						
33. At least one of our project group members has had very extensive educational experience ata foreign university on subject matter that is relevant to this project.						
34. At least one of our project group members had very extensive educational experience ata domestic university on subject matter that is relevant to this project.						
35. At least one of our project group members had very extensive working experience abroad on subject matter that relevant to this project.						
36. At least one of our project group members had very extensive working experience with our targeted customers on subject matter that is relevant to this project.						
37. At least one of our project group members had very extensive working experience with other projects within NSTDA on subject matter that is relevant to this project.						
38. Prior to the start of our project, our project group generated a lot of patents and publications that are relevant to this project.						
39. Based on the results of this project, do you think that the targeted customers of this project will have another collaborative project with your project group in the near future?						

B.3 General information about the expected results of this project

QUESTIONS	ANSWERS
<p>40. Has any income (in kind or in cash) resulted from this project? And, is any income expected to result from this project?</p>	<p>.....Yes/No..... Yes/No.....</p>
<p>41. Have any publications in peer-reviewed journals resulted from this project? Have you submitted any manuscripts for publication in peer-reviewed journals? And, do you expect this project to yield any publications in peer-reviewed journals?</p>	<p>.....Yes/No..... Yes/No..... Yes/No.....</p>
<p>42. Did any patents result from this project? Have you filed for any patents that are based on work that was conducted for this project? And, do you expect this project to yield any patents?</p>	<p>.....Yes/No..... Yes/No..... Yes/No.....</p>

APPENDIX C: DATA ANALYSIS

The appendix presents the details of statistical tools that are used in Chapter 5.

C.1 Exploratory Factor Analysis

Exploratory factor analysis can be used to “analyze the underlying pattern for a number of variables. It determines whether the variables can be condensed or summarized in a smaller set of factors or constructs. The exploratory factor analysis has “three main uses: (1) to understand the structure of the latent variable (2) to construct a questionnaire to measure and underlying variables and (3) to reduce a data set to a more manageable size while retaining as much of the original information as possible” (Field, 2005, p. 619) Also, this study will measure **factor loading of each item**. Field (2005) states “the factor loading can be thought of as the Pearson correlation between a factor and a variable. ... If we square the factor loading we obtain a measure of the substantive importance of a particular variable to a factor” (Field, 2005, p. 622). Thus, the item or variable will be measured to identify the importance of that specific variable to a latent factor in this study.

C.2 Correlation Analysis

C.2.1 Pearson's Correlation Coefficient

To assess the degree of interdependence between variables, this study will consider both statistical significance and the correlation coefficient. Pearson's correlation coefficient is the most common measure of effect size. It is controlled to lie between -1 and 1 (Field, 2005, p. 111). The effect size provides an objective measure between variables. J. Cohen *et al.*, 2003, suggested the value of $\pm .10$ for small size effect that can explain 1% of the total variance, $\pm .30$ for medium effect that the effect can explain 9% of the total variance, $\pm .50$ for large effect that accounts for 25% of total variance, and the value of .00 for no effect (cited by Field, 2005, p. 32). This study will also identify the size of effects on each pair of variables to ensure the importance of the effects before doing more analysis. This correlation matrix will be extremely useful for getting an idea of the relationships between dependent variables and independent variables.

C.2.2 Statistical Significance

“One-tailed tests should be used when there is a specific direction to the hypothesis being tested, and two-tailed tests should be used when a relationship is expected, but the direction of the relationship is not predicted” (Field, 2005, p. 125). In this study, I use two-tailed tests for analysis of Pearson's correlation coefficient because the direction of external engagement on projects' performance may be presented in both positive and

negative directions. Also, the cut-off point of less than .05 is the general criterion for statistical significance (Field, 2005).

C.3 Regression Analysis: multiple regression and logistic regression

To determine the relative impact of the independent variables on the dependent variable, this study use regression analyses of multiple regression and logistic regression. “Multiple regression is an extension of simple regression in which an outcome is predicted by a linear combination of two or more predictor variables.

The form of the model is
$$Y_i = (b_0 + b_1X_1 + b_2X_2 + \dots + b_nX_n) + \epsilon_i$$
 in which the outcome is denoted as Y, and each predictor is denoted as X.

Each predictor has a regression coefficient b_i associated with it, and b_0 is the value of the outcome when all predictors are zero” (Field, 2005, p. 738). From the model, b_i can be used to define the relative importance of the predictor on the outcome. It means for every a unit change in X_i , Y_i goes up by about b_i . Also, comparing b_i of the predictors will see the relative impact of the predictors on the outcome.

Logistic regress is “a version of multiple regression in which the outcome is dichotomous” (Field, 2005, p. 736).

The form of the model is $P(Y) = \frac{1}{1+e^{-(b_0+b_1X_1+b_2X_2+\dots+b_nX_n+i)}}$ in which the probability of Y occurring is denoted as P(Y), e is the base of natural logarithms, and the other coefficients are the same as in multiple regression (Field, 2005, p. 220).

From the model, to interpret logistic regression we use the value of $\exp b_i$ or $Exp (B_i)$ in the regression table. $Exp (B_i)$ is an indicator of the change in odds resulting from a unit change in the predictor and is similar to b_i in multiple regression. “If the value of $Exp (B_i)$ greater than 1 then it indicates that as the predictor increase the odds of the outcome occurring increase (Field, 2005, p. 225). For example, if the value of $Exp (B_i)$ is 54.36 for the impact of engagement with LTUs on the success in technology commercialization, it means the odds of a project succeeded in technology commercialization are 54.36 times greater for a project who had the degree of engagement with LTUs of 5 in Likert scale, than for a project whose the degree of engagement was 4 in Likert scale (adapted from Burns & Burns, 2008, p. 574).

In the regression analysis, this study also applies backward stepwise method in the model that includes many predictors in the analysis, in particular, the model that includes variables pertaining to interaction variables. The backward method calculates the contribution of each predictor on the outcome by comparing the significance value or the t-test of each predictor against a removal criterion. If a predictor meets the removal criterion or does not improve the prediction power of the model, then it is removed from the analysis. Then the model re-assessed the remaining predictors. Field (2005) also mentioned “the backward method runs lower risk of missing a predictor that predicts the

outcome than the forward method” (Field, 2005, pp. 160-161) and it works when there are many predictors in the model.

C.3.1 R^2

“The correlation coefficient squared or the coefficient of determination (R^2) is a measure of the amount of variability in one variable that is explained by the other” (Field, 2005, p. 128). If we square a correlation coefficient between a pair of variables, the value of R^2 will tell us how much of the variability in one variable can be explained by the other. This study will use R^2 to tell us how much the effects of the variability in a dependent variable can be explained by an independent variable.

In logistic regression, Cox & Snell R^2 and Nagelkerke’s R^2 attempt to imitate the R^2 in a multiple regression. However, “based on ‘likelihood’, the maximum of Cox & Snell R^2 can be (and usually is) less than 1.0, making it difficult to interpret. Nagelkerke’s R^2 modification ranges from 0 to 1 is a more reliable measure of the relationship” (Burns & Burns, 2008, p. 580). The value of Cox & Snell R^2 and Nagelkerke’s R^2 can indicate percentage of variation in the dependent variable is explained by the logistic model. Also, normally the Nagelkerke’s R^2 is higher than the Cox & Snell R^2 .

C.3.2 Adjusted R^2

The adjusted R^2 can be used to assess how well the model is able to predict the outcome in a different sample. Field, 2005 (p. 171) mentions cross-validation is a way to assess the accuracy of a model across different samples. He also mentions “if a model can be

generalized, then it must be capable of accurately predicting the same outcome variable from the same set of predictors in a different group of people. If the model is applied to a different sample and there is *a severe drop in its prediction power*, then the model clearly does not generalize.” In regression, the value of adjusted R^2 should be very close to the value of R^2 . “The value of R^2 presents how much of the variance in the outcome is accounted for by the regression model from the sample. The value of adjusted R^2 presents how much the variance in the outcome would be accounted for if the model is derived from the population from which the sample was taken ... the comparable value indicates that the cross-validity of the model is very good” (Field, 2005, p. 172). In case that “the value of adjusted R^2 is smaller than the value of R^2 , the reduction shows if the model were derived from the population rather than a sample. It would account for less variance in the outcome at the reduction value” (Field, 2005, p. 188). In addition, the value of R^2 typically increases when we add more independent variables in the model. Increasing the R^2 doesn't mean that the model increases the power to predict the outcome. Adjusted R^2 is used to compensate for the addition of variables to the model. When there are numbers of independent variables, the value of adjusted R^2 should be reported for the explanatory power of the model.

C.3.3 F-Ratio

The F-ratio is a measure of the ratio of the variation explained by the model and the variation explained by observed data (Field, 2005, p. 150 and 323). That means F-ratio is “a measure of how much the model has improved the prediction of the outcome compared to the level of inaccuracy of the model” (Field, 2005, p. 150). Field, 2005, also

mentions a good model should have F-ratio greater than 1. It means the improvement in prediction from the model should be large and the difference between the model and the observe data should be small. The increasing of F-ratio can interpret as the model significantly improves the ability to predict the dependent variable (Field, 2005, p. 190). In logistic regression, “chi-square statistic measures the difference between the model as it currently stands and the model when only the constant is included” (Field, 2005, p. 237). Also, if the value of chi-square is significant at lower than .05 level, we can say that overall the model is predicting the outcome significantly better than it was with only the constant included. “The model chi-square is an analogous of the F-test for the linear regression” (Field, 2005, p. 238). Accordingly, chi-square statistic will be used to assess how much better the model predicts the outcome variable in logistic regression.

C.4 Interaction Effects

Interaction effects represent the combined effects of variables on the criterion or dependent measure (Aiken & West, 1991). “When an interaction effect is present, the impact of one variable depends on the level of the other variable. Part of the power of multiple regression is the ability to estimate and test interaction effects when the predictor variables are either categorical or continuous” (J. J. Stevens, 2011).

To test whether or not moderating variables including prior experience, prior knowledge, and PILAs impact the relationship between the engagement with external sources of knowledge and project performance, this study will use multiple regression analyses and

follow the procedure of analysis in the interaction effects by Aiken & West, 1991; Lichtenthaler, 2006b; Dawson, 2006.

The regression equation that contains the interaction would be written as:

$$Y = b_0 + b_1X + b_2Z + b_3(X*Z) \text{ ----- (Aiken \& West, 1991, p. 9)}$$

Y = Dependent variable (DV)

X = Independent variable (IV)

Z = Moderating variable (MV)

b₀ = Intercept / Constant

b₁ = Unstandardised regression coefficient of IV

b₂ = Unstandardised regression coefficient of MV

b₃ = Unstandardised regression coefficient of interaction

In these following examples, I create a set of invented data in table VII, and then follow the processes of Dawson, 2006, and Aiken & West, 1991 to present two examples of how to calculate the interaction effect. The process of Dawson, 2006 helps in the generation of data in a spreadsheet as presented in table C.1 and C.3. The process suggested by Aiken & West, 1991 helps in the presentation of two simple slopes, see figure C.1.

Table C.1: An example of input statistical data for equation (adapted from Dawson, 2006)

Unstandardised Regression Coefficients:	
Independent variable (b ₁)	1.069
Moderator (b ₂)	0.352
Interaction (b ₃)	-0.195
Intercept / Constant (b ₀)	2.658
Means / SDs of variables:	
Mean of independent variable (Mean _x)	0
SD of independent variable (S _x)	1
Mean of moderator (Mean _z)	0
SD of moderator (S _z)	1.645

Table C.2: an example of calculation (adapted from Dawson, 2006)

	Low independent variable	High independent variable
Low moderating variable	$Y_{LL} = b_0 + b_1(\text{Mean}_X - S_X) + b_2(\text{Mean}_Z - S_Z) + b_3((\text{Mean}_X - S_X) * (\text{Mean}_Z - S_Z))$ <p style="text-align: right;">= 0.689</p>	$Y_{LH} = b_0 + b_1(\text{Mean}_X + S_X) + b_2(\text{Mean}_Z - S_Z) + b_3((\text{Mean}_X + S_X) * (\text{Mean}_Z - S_Z))$ <p style="text-align: right;">= 3.468</p>
High moderating variable	$Y_{HL} = b_0 + b_1(\text{Mean}_X - S_X) + b_2(\text{Mean}_Z + S_Z) + b_3((\text{Mean}_X - S_X) * (\text{Mean}_Z + S_Z))$ <p style="text-align: right;">= 2.489</p>	$Y_{HH} = b_0 + b_1(\text{Mean}_X + S_X) + b_2(\text{Mean}_Z + S_Z) + b_3((\text{Mean}_X + S_X) * (\text{Mean}_Z + S_Z))$ <p style="text-align: right;">= 3.985</p>

Table C.3: X and Y coordinates (adapted from Dawson, 2006)

	X	Y
Low moderating with low independent variable	-1	0.689
Low moderating with high independent variable	1	3.468
High moderating with low independent variable	-1	2.489
High moderating with high independent variable	1	3.985

Also, Aiken & West, 1991 (p. 14) suggested a procedure to interpret the interaction effects by generating simple linear equations and simple slopes as follows:

From $Y = b_0 + b_1X + b_2Z + b_3(X*Z)$

$$Y_{Z_LOW} = 2.658 + 1.069X + .0352Z + (-.195(X*Z))$$

At $Z = S_{Z_LOW} = 0 - 1.645$: $Y_{Z_LOW} = \mathbf{1.389X + 2.079}$

$$Y_{Z_HIGH} = 2.658 + 1.069X + .0352Z + (-.195(X*Z))$$

At $Z = S_{Z_HIGH} = 0 + 1.645$: $Y_{Z_HIGH} = \mathbf{.748X + 3.237}$

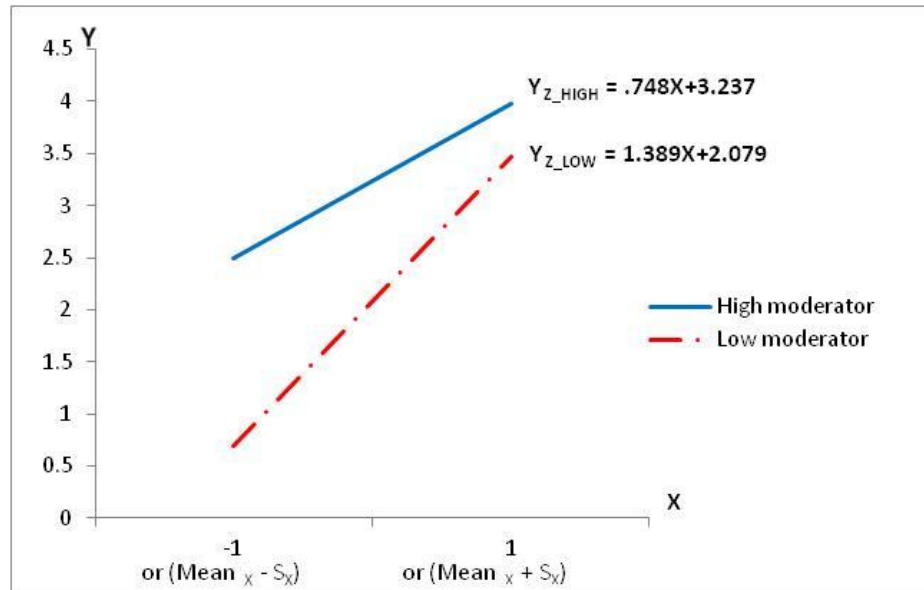


Figure C.1: An example of simple slopes for interaction analysis (adapted from Aiken & West, 1991)

C.5. Benchmarking Metrics for Regression Models

C.5.1 Benchmarking Metrics for Multiple-Regression Models

- R^2 is a measure of how much the effects of the variability in a dependent variable can be explained by a set of independent variables (IVs).
- Adjusted R^2 is used to compensate R^2 when there are numbers of IVs in the model. As adding more IVs, R^2 normally increase. If the additional IVs have little correlations to output, adjusted R^2 should be reported for the explanatory power of the model

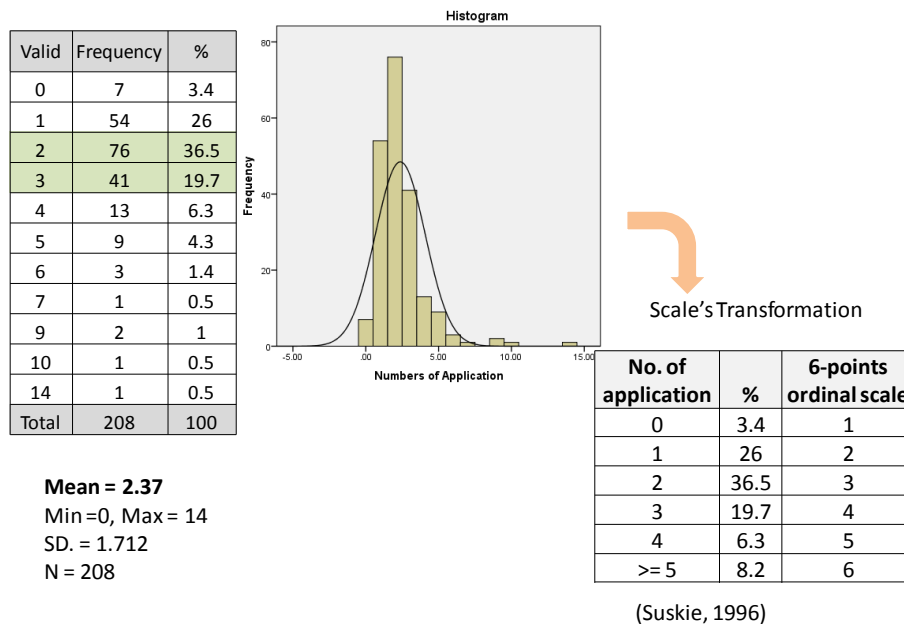
- F-ratio is a measure of how much the model has improved the prediction of the outcome compared to the level of inaccuracy of the model. If the model significantly improves the ability to predict the outcome, F-ratio should be greater than 1 at significant level lower than .05

C.5.2 Benchmarking Metrics for Logistic Regressions

- Cox & Snell R^2 is a version of R^2 for logistic regression, but the maximum of Cox & Snell R^2 usually is less than 1.0. This makes it difficult to interpret.
- Nagelkerke's R^2 is also a version of R^2 for logistic regression. The value of Nagelkerke's R^2 ranges from 0 to 1 and is more reliable than Cox & Snell R^2 . The value of Nagelkerke's R^2 can indicate percentage of variation in the outcome explained by the logistic model.
- Chi-square is a version of F-ratio for logistic regression. Chi-square presents the improvement in prediction of the outcome between the model as it currently stands and the model when only the constant is included.
- % correct is a measure of how much the model can correctly classify cases.

APPENDIX D: VERSATILITY OF TECHNOLOGY

The figure below presents a process for transformation of scale from objective data into an ordinal scale³¹. Multiple choices of industry applications for versatility of technology (OV3.3) are described in appendix B. The number of strategic programs in which the output of the project can be applied is translated into an ordinal scale that consists of the following six classes: 1 means the output could not be applied in any strategic program; 2 means the output could be applied in one strategic program; 3 means the output could be applied in two strategic programs, 4 means the output could be applied in three strategic programs, 5 means the output could be applied in 4 strategic programs, and 6 means the output could be applied in more than four strategic programs.



³¹ In the ordinal scale, the difference between point 1 and 2 is not necessarily the same as the distance between point 3 and 4, but the values need to be totally ordered (Suskie, 1996).

APPENDIX E: CORRELATION MATRIX

	OV1	OV2	OV3.1	OV3.2	OV3.3	IV1	IV2	IV3	IV4	IV5	IV6	IV7	IV8	IV9	IV10	IV11	IV12
Mission 1: User Satisfaction [OV1]	1																
Mission 2: Probability of Commercialization of Technology [OV2]	.580**	1															
Mission 3.1: Probability of Generating Publication [OV3.1]	-.206**	-.389**	1														
Mission 3.2: Probability of Generating a Patent [OV3.2]	-.077	-.162*	.167*	1													
Mission 3.3: Versatility of Technology [OV3.3]	-.061	-.123	.224**	.050	1												
Contextual learning with other R&D units 1 [IV1_ORDU_CLA1]	-.100	-.006	.098	.034	.119	1											
Contextual learning with local universities 1 [IV2_LocUniv_CLA1]	.125	.104	.042	-.014	-.082	.209**	1										
Contextual learning with inter sources 1 [IV3_InatSrc_CLA1]	-.031	-.141*	.286**	.081	.139*	-.048	.126	1									
Contextual learning with technology users 1 [IV4_LTUs_CLA1]	.428**	.257**	-.114	.065	-.071	-.035	.065	.105	1								
Contextual learning with other R&D units 2 [IV5_ORDU_CLA2]	-.070	-.098	.144*	.082	.214**	.614**	.238**	.149*	-.112	1							
Contextual learning with local universities 2 [IV6_LocUniv_CLA2]	.085	.002	.217**	.090	.064	.143	.568**	.132	.080	.324**	1						
Contextual learning with inter sources 2 [IV7_InatSrc_CLA2]	-.037	-.067	.371**	.035	.193**	.035	.094	.690**	.065	.142*	.204**	1					
Contextual learning with technology users 2 [IV8_LTUs_CLA2]	.465**	.319**	-.134	.069	-.084	-.083	.029	.130	.625**	.003	.131	.194**	1				
Vicarious learning with other R&D units 1 [IV9_ORDU_VLA1]	-.061	-.152	.247**	.087	.118	.417**	.072	.149*	.091	.452**	.159	.224**	.170*	1			
Vicarious learning with local universities 1 [IV10_LocUniv_VLA1]	-.006	.054	.181**	.012	.066	.124	.343**	-.028	.057	.233**	.476**	.035	.062	.233**	1		
Vicarious learning with inter sources 1 [IV11_InatSrc_VLA1]	-.233**	-.202**	.289**	-.132	.238**	.092	.069	.187**	-.184**	.060	.116	.272**	-.120	.036	.152*	1	
Vicarious learning with production units 1 [IV12_LTUsPU_VLA1]	.582**	.626**	-.215**	-.038	-.085	.003	.014	-.146**	.319**	-.045	.048	-.003	.449**	.028	.140*	-.129	1
Vicarious learning within end users 1 [IV13_LTUsEU_VLA1]	.492**	.406**	-.292**	.031	.002	-.019	.115	-.198**	.202**	.024	.157	-.184**	.244**	-.114	.064	-.239**	.444**
Vicarious learning with other R&D units 2 [IV14_ORDU_VLA2]	-.113	-.187**	.214**	.180**	.216**	.378**	.077	.174*	-.018	.476**	.201**	.213**	.086	.765**	.249**	-.014	-.025
Vicarious learning with local universities 2 [IV15_LocUniv_VLA2]	-.004	-.021	.244**	.085	.108	.193**	.351**	.098	.054	.255**	.407**	.079	-.006	.183**	.804**	.144	.088
Vicarious learning with inter sources 2 [IV16_InatSrc_VLA2]	-.150**	-.157**	.281**	-.058	.169**	.103	.044	.241**	-.184**	.066	.100	.248**	-.137**	.010	.123	.756**	-.132
Vicarious learning with production units 2 [IV17_LTUsPU_VLA2]	.620**	.658**	-.238**	-.038	-.071	-.053	-.014	-.166**	.329**	-.103	.007	-.039	.465**	-.085	.042	-.210**	.898**
Vicarious learning within end users 2 [IV18_LTUsEU_VLA2]	.524**	.465**	-.329**	-.042	-.011	-.083	.036	-.235**	.241**	-.055	.085	-.251**	.255**	-.224**	-.065	-.310**	.389**
Prior knowledge in core technology [MV1_PreKn_Core]	.276**	.219**	.129	.081	.099	.061	.070	.065	.055	-.031	.152	.160*	.070	.152*	.026	-.153	.274**
Prior knowledge in journal publications [MV2_PreKn_Jr]	-.097	-.108	.418**	-.096	.160*	.052	-.050	.257**	-.157**	.049	.094	.321**	-.065	.081	.023	.185**	.016
Prior knowledge in patents [MV4_PreKn_Pat]	-.067	.043	-.016	.116	.084	.071	.087	.001	.064	.088	.167**	.044	.085	.018	.079	.010	.070
Project internal learning activities 1 [MV5_PILA1]	.081	-.028	.087	.046	.088	-.015	.008	.112	.197**	.030	.131	.148*	.171*	.179**	.133	.242**	.089
Project internal learning activities 2 [MV6_PILA2]	.136	.134	.055	.017	.023	.007	-.026	.083	.244**	-.082	.043	.142*	.204**	.148*	.079	.211**	.238**
Project internal learning activities 3 [MV7_PILA3]	.152**	.096	.031	.034	.137**	-.003	.032	.137**	.249**	-.013	.066	.086	.165*	.146*	.134	.192**	.236**
Project internal learning activities 4 [MV8_PILA4]	.123	.035	.085	-.020	.224**	-.039	.049	.203**	.185**	-.001	.068	.210**	.177**	.104	.018	.243**	.159**
Prior experience in education from international sources of knowledge [MV9_PrExp_Ed_InatSrc]	-.094	-.115	.204**	.061	.122	-.004	-.094	.266**	-.030	-.025	.014	.273**	-.039	.086	-.006	.274**	-.026
Prior experience in education from local sources of knowledge [MV10_PrExp_Ed_LocUniv]	.238**	.145*	-.018	.093	-.018	-.007	.123	.033	.279**	-.007	.070	-.015	.267**	.028	.269**	-.054	.249**
Prior experience in working from international sources of knowledge [MV11_PrExp_Vk_InatSrc]	-.019	.048	.193**	-.120	.242**	-.119	-.124	.151*	-.065	-.160**	-.010	.277**	-.081	-.159*	.098	.484**	.047
Prior experience in working with local technology users [MV12_PrExp_Vk_LTUs]	.481**	.481**	-.173**	-.133	.013	-.087	-.003	-.043	.318**	-.223**	-.059	.048	.307**	-.119	.005	-.122	.441**
Prior experience in working with other R&D units [MV13_PrExp_Vk_ORDU]	.055	.150*	-.037	.057	-.004	.451**	.133	.041	.097	.338**	.025	.030	.155*	.366**	.062	-.066	.070
Prior knowledge level of project group [MV14_PreKn_Lev]	.000	-.047	.249**	-.093	.085	.146*	.002	.246**	-.081	.124	.134	.311**	.012	.149*	.057	.156*	.138**

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

Appendix E: Correlation Matrix (cont.)

	IV13	IV14	IV15	IV16	IV17	IV18	MV1	MV2	MV4	MV5	MV6	MV7	MV8	MV9	MV10	MV11	MV12	MV13	MV14
OV1																			
OV2																			
OV3.1																			
OV3.2																			
OV3.3																			
IV1																			
IV2																			
IV3																			
IV4																			
IV5																			
IV6																			
IV7																			
IV8																			
IV9																			
IV10																			
IV11																			
IV12																			
IV13	1																		
IV14	-.082	1																	
IV15	.001	.307**	1																
IV16	-.226**	.050	.194**	1															
IV17	.388**	-.115	-.001	-.219**	1														
IV18	.848**	-.155*	-.088	-.305**	.496**	1													
MV1	.150*	.098	.055	-.060	.286**	.132	1												
MV2	-.196**	.062	.098	.253**	-.025	-.229**	.263**	1											
MV4	.018	.102	.143*	.098	.036	.029	.159*	.241**	1										
MV5	.058	.082	.066	.256**	-.013	-.006	.047	.110	.041	1									
MV6	.083	.050	-.002	.220**	.154*	.025	.162*	.098	.090	.727**	1								
MV7	.134	.077	.087	.217**	.177*	.093	.168*	.126	.039	.628**	.675**	1							
MV8	.024	.038	.010	.258**	.103	.010	.217**	.191**	.030	.611**	.576**	.775**	1						
MV9	-.288**	.096	.023	.263**	-.021	-.240**	.279**	.332**	.185**	.250**	.275**	.195**	.353**	1					
MV10	.180**	.096	.325**	.013	.221**	.180**	.078	.070	.143*	.087	.116	.171	.169*	.076	1				
MV11	-.183**	-.072	.088	.421**	.037	-.149*	.054	.249**	-.032	.240**	.279**	.294**	.375**	.420**	.086	1			
MV12	.185**	-.148*	-.065	-.142*	.520**	.266**	.229**	.037	-.013	.045	.186**	.193**	.185**	.069	.186**	.247**	1		
MV13	.046	.340**	.056	-.041	.081	.029	.106	.080	.072	-.146*	.023	.103	.060	-.058	.189**	-.201**	.105	1	
MV14	-.089	.072	.105	.257**	.073	-.093	.300**	.638**	.355**	.266**	.210**	.200**	.253**	.378**	.115	.168**	.066	.069	1

** . Correlation is significant at the 0.01 level (2-tailed).

* . Correlation is significant at the 0.05 level (2-tailed).

APPENDIX F: FACTOR ANALYSIS

Factors	FMV1	FIV1	FIV2	FIV3	FIV4	FIV5	FIV6	FMV2	FIV7	FIV8	FIV9	FMV3	FMV4	FMV5	FMV6	FMV7	FMV8
Cronbach's Alpha	0.887	0.946	0.859	0.891	0.916	0.867	0.816	0.773	0.769	0.76	0.723	-	-	-	-	-	-
Descriptive statistics: Min	-2.442	-2.129	-1.680	-1.826	-2.073	-1.736	-3.210	-1.639	-2.762	-2.330	-2.032	-2.096	-2.133	-2.767	-3.720	-2.793	-2.969
Descriptive statistics: Max	2.341	2.386	2.928	3.046	2.488	3.260	2.175	2.393	2.569	3.947	3.939	2.247	2.502	1.697	1.990	1.686	3.082
Variables:																	
MV7_PILA3	.899																
MV8_PILA4	.847																
MV5_PILA1	.805																
MV6_PILA2	.793																
IV12_LTUsPU_VLA1		.909															
IV17_LTUsPU_VLA2		.892															
IV16_InatSrc_VLA2			.884														
IV11_InatSrc_VLA1			.883														
IV10_LocUniv_VLA1				.907													
IV15_LocUniv_VLA2				.906													
IV13_LTUsEU_VLA1					.903												
IV18_LTUsEU_VLA2					.892												
IV14_ORDU_VLA2						.897											
IV9_ORDU_VLA1						.872											
IV3_InatSrc_CLA1							.895										
IV7_InatSrc_CLA2							.846										
MV2_PrKn_Jr								.860									
MV14_PrKn_Lev								.852									
IV4_LTUs_CLA1									.875								
IV8_LTUs_CLA2									.761								
IV1_ORDU_CLA1										.883							
IV5_ORDU_CLA2										.743							
IV2_LocUniv_CLA1											.891						
IV6_LocUniv_CLA2											.740						
MV12_PrExp_Wk_LTUs												.852					
MV13_PrExp_Wk_ORDU													.905				
MV1_PrKn_Core														.906			
MV10_PrExp_Ed_LocUniv															.928		
MV9_PrExp_Ed_InatSrc																.889	
MV11_PrExp_Wk_InatSrc			.439														.503
% of Total Variance	10.383	7.005	6.678	6.525	6.445	6.435	5.827	5.743	5.295	5.215	5.061	3.587	3.504	3.353	3.322	3.287	2.042
Cumulative % of Variance	10.383	17.389	24.067	30.592	37.037	43.473	49.299	55.043	60.337	65.553	70.613	74.200	77.704	81.057	84.379	87.666	89.708
Extraction Method: Principal Component Analysis.				Rotation Method: Varimax with Kaiser Normalization.													

APPENDIX G: REGRESSION ANALYSIS

G.1 Regression Analysis for Mission-1: User Satisfaction

Factors	1. Knowledge Inflow Baseline					2.1 Project Group Baseline					2.2 Intra-Organization Baseline					3. Integrated Model					4. Interaction Model				
	B	S. E.	Beta	t	Sig.	B	S. E.	Beta	t	Sig.	B	S. E.	Beta	t	Sig.	B	S. E.	Beta	t	Sig.	B	S. E.	Beta	t	Sig.
(Constant)	3.886	.080		48.526	.000	3.981	.105		37.825	.000	3.981	.105		37.825	.000	3.885	.073		53.116	.000	3.868	.063		61.146	.000
FMV3_PrExp_Wk_LTUs						.329	.104	.221	3.170	.002	.329	.104	.221	3.170	.002	.366	.072	.246	5.088	.000	.436	.066	.294	6.613	.000
FMV5_PrKn_Core						.206	.105	.137	1.964	.051	.206	.105	.137	1.964	.051	.170	.073	.114	2.350	.020	.109	.065	.073	1.668	.097
FMV6_PrExp_Ed_LocUniv																.178	.072	.119	2.464	.015					
FMV1_PILAs																.153	.073	.101	2.086	.038	.210	.066	.138	3.185	.002
FIV1_LTUsPU_VLAs	.707	.079	.472	8.900	.000											.710	.072	.474	9.794	.000	.769	.065	.514	11.798	.000
FIV4_LTUsEU_VLAs	.591	.079	.398	7.504	.000											.591	.072	.398	8.233	.000	.478	.065	.322	7.408	.000
FIV7_LTUs_CLAs	.497	.080	.329	6.205	.000											.513	.073	.340	7.023	.000	.480	.071	.318	6.738	.000
FIV9_LocUniv_CLAs	.167	.080	.110	2.081	.039											.159	.073	.105	2.177	.031	.158	.065	.104	2.414	.017
FIV2_InatSrc_VLAs																-.127	.072	-.085	-1.766	.079	-.167	.065	-.112	-2.559	.011
FIV9_LocUniv_CLAs_X_FMV4_PrExp_Wk_ORDU																					.227	.075	.136	3.023	.003
FIV3_LocUniv_VLAs_X_FMV5_PrKn_Core																					.202	.068	.133	2.979	.003
FIV5_ORDU_VLAs_X_FMV2_PrKn_PJ																					.190	.068	.124	2.795	.006
FIV2_InatSrc_VLAs_X_FMV5_PrKn_Core																					.189	.061	.140	3.072	.002
FIV9_LocUniv_CLAs_X_FMV3_PrExp_Wk_LTUs																					.179	.063	.131	2.852	.005
FIV5_ORDU_VLAs_X_FMV4_PrExp_Wk_ORDU																					-.234	.068	-.157	-3.441	.001
FIV1_LTUsPU_VLAs_X_FMV3_PrExp_Wk_LTUs																					-.164	.067	-.108	-2.440	.016
FIV7_LTUs_CLAs_X_FMV4_PrExp_Wk_ORDU																					-.158	.065	-.106	-2.437	.016
FIV4_LTUsEU_VLAs_X_FMV3_PrExp_Wk_LTUs																					-.155	.067	-.108	-2.312	.022
FIV1_LTUsPU_VLAs_X_FMV4_PrExp_Wk_ORDU																					-.151	.067	-.101	-2.268	.025
FIV7_LTUs_CLAs_X_FMV1_PILAs																					-.149	.065	-.104	-2.292	.023
FIV4_LTUsEU_VLAs_X_FMV8_PrExp_Wk_InatSrc																					-.144	.065	-.097	-2.207	.029
FIV2_InatSrc_VLAs_X_FMV1_PILAs																					-.119	.065	-.085	-1.835	.068
FIV5_ORDU_VLAs_X_FMV1_PILAs																					.125	.066	.083	1.881	.062
R ²					.469					.069					.069					.571					.703
R ² adjust					.458					.059					.059					.550					.665
F					41.705**					7.042**					7.042**					27.175***					18.385***
No.					193					193					193					193					193
ΔR ² adjust					-					-					0.000					0.491					0.606

Note:

- 1) The lower sample size of 193 samples results from respondents not being able to answer the question pertaining to mission1 (OV1) in the survey.
- 2) In model 4, the three factors excluded before regression include a) FIV8_ORDU_CLAs and its interactions, b) FMV6_PrExp_Ed_LocUniv and its interactions, and c) FMV7_PrExp_Ed_InatSrc and its interactions, because they tend to have less power to predict output variables in all models.
- 3) Some variables with $p > .05$ are included in the regression because they still improve the prediction power of the model or do not meet the removal criterion of stepwise backward, see appendix C.3.

G.2 Regression Analysis for Mission 2: Probability of Commercialization of Technology

Factors	1. Knowledge Inflow Baseline					2.1 Project Group Baseline					2.2 Intra-Organization Baseline					3. Integrated Model					4. Interaction Model				
	B	S.E.	Wald	Exp(B)	Sig.	B	S.E.	Wald	Exp(B)	Sig.	B	S.E.	Wald	Exp(B)	Sig.	B	S.E.	Wald	Exp(B)	Sig.	B	S.E.	Wald	Exp(B)	Sig.
(Constant)	-1.108	.183	.348	.898	.555	-.110	.147	.563	.896	.453	-.110	.149	.541	.896	.462	-.249	.215	1.343	.780	.246	-.704	.357	3.882	.495	.049
FMV3_PrExp_Wk_LTUs						.599	.155	14.979	1.819	.000	.630	.160	15.439	1.878	.000	1.006	.216	21.624	2.736	.000	1.627	.353	21.220	5.087	.000
FMV4_PrExp_Wk_ORDU						.292	.152	3.713	1.339	.054	.318	.159	3.992	1.374	.046	.509	.224	5.150	1.664	.023					
FMV5_PrKn_Core						.246	.149	2.722	1.278	.099	.250	.150	2.762	1.284	.097	.415	.204	4.161	1.515	.041	1.985	.553	12.893	7.277	.000
FIV1_LTUsPU_VLAs	1.581	.221	51.272	4.859	.000											1.820	.254	51.385	6.173	.000	3.996	.683	34.184	54.365	.000
FIV4_LTUsEU_VLAs	.834	.196	18.174	2.302	.000											1.072	.242	19.679	2.921	.000	2.731	.590	21.431	15.353	.000
FIV9_LocUniv_CLAs																					1.019	.340	8.968	2.770	.003
FIV7_LTUs_CLAs																.435	.230	3.570	1.545	.059	.907	.366	6.134	2.477	.013
FIV5_ORDU_VLAs	-5.81	.197	8.734	.559	.003						-.402	.154	6.769	.669	.009	-.700	.226	9.597	.496	.002	-1.500	.381	15.521	.223	.000
FIV7_LTUs_CLAs_X_FMV3_PrExp_Wk_LTUs																					1.426	.378	14.220	4.160	.000
FIV5_ORDU_VLAs_X_FMV5_PrKn_Core																					1.332	.500	7.088	3.789	.008
FIV6_InatSrc_CLAs_X_FMV5_PrKn_Core																					1.117	.407	7.522	3.054	.006
FIV5_ORDU_VLAs_X_FMV2_PrKn_PJ																					.871	.368	5.609	2.388	.018
FIV9_LocUniv_CLAs_X_FMV3_PrExp_Wk_LTUs																					.870	.271	10.336	2.386	.001
FIV9_LocUniv_CLAs_X_FMV2_PrKn_PJ																					.674	.320	4.423	1.961	.035
FIV4_LTUsEU_VLAs_X_FMV5_PrKn_Core																					-1.410	.569	6.136	.244	.013
FIV1_LTUsPU_VLAs_X_FMV5_PrKn_Core																					-1.201	.467	6.598	.301	.010
FIV7_LTUs_CLAs_X_FMV5_PrKn_Core																					-.895	.408	4.812	.409	.028
FIV7_LTUs_CLAs_X_FMV1_PILAs																					-.842	.375	5.043	.431	.025
FIV2_InatSrc_VLAs_X_FMV5_PrKn_Core																					-.833	.370	5.061	.435	.024
FIV2_InatSrc_VLAs_X_FMV1_PILAs																					-.750	.322	5.408	.472	.020
FIV3_LocUniv_VLAs_X_FMV5_PrKn_Core																					.724	.400	3.271	2.063	.071
FIV4_LTUsEU_VLAs_X_FMV8_PrExp_Wk_InatSrc																					.479	.299	2.566	1.614	.109
Cox&Snell R ²					.384					.102					.133					.485					.604
Nagelkerke ²					.512					.136					.177					.648					.807
Chi-square					100.728***					22.419***					29.568***					138.714***					192.909***
Percentage correct					80.3					66.3					69.7					86.1					92.3
No.					208					208					208					208					208
ΔCox&Snell R ²					-					-					0.031					0.383					0.502
ΔNagelkerke ²					-					-					0.041					0.512					0.671

Note:

- 1) In model 4, the three factors excluded before regression include a) FIV8_ORDU_CLAs and its interactions, b) FMV6_PrExp_Ed_LocUniv and its interactions, and c) FMV7_PrExp_Ed_InatSrc and its interactions, because they tend to have less power to predict output variables in all models.
- 2) Some variables with $p > .05$ are included in the regression because they still improve the prediction power of the model or do not meet the removal criterion of stepwise backward, see appendix C.3.

G.3 Regression Analysis for Mission-3--Criterion-1: Probability of Generating a Publication

Factors	B	S.E.	Wald	Exp(B)	Sig.	B	S.E.	Wald	Exp(B)	Sig.	B	S.E.	Wald	Exp(B)	Sig.	B	S.E.	Wald	Exp(B)	Sig.	B	S.E.	Wald	Exp(B)	Sig.
(Constant)	-1.039	.191	29.726	.354	.000	-.836	.163	26.446	.434	.000	-.861	.166	26.799	.423	.000	-1.071	.203	27.809	.343	.000	-1.376	.269	26.224	.253	.000
FMV2_PrKn_PJ						.612	.155	15.568	1.844	.000	.634	.159	15.979	1.885	.000	.833	.203	16.883	2.300	.000	.526	.254	4.276	1.692	.039
FMV5_PrKn_Core						.375	.178	4.467	1.456	.035	.398	.185	4.626	1.488	.031	.446	.198	5.063	1.562	.024					
FMV8_PrExp_Wk_InatSrc						.318	.160	3.942	1.375	.047	.323	.163	3.947	1.381	.047	.416	.186	4.986	1.516	.026	.608	.237	6.588	1.836	.010
FMV4_PrExp_Wk_ORDU																					-.462	.271	2.908	.630	.088
FIV6_InatSrc_CLAs	.690	.197	12.266	1.994	.000											.802	.217	13.645	2.231	.000	.816	.256	10.174	2.262	.001
FIV3_LocUniv_VLAs	.556	.180	9.558	1.743	.002											.713	.214	11.123	2.040	.001	.527	.249	4.473	1.694	.034
FIV2_InatSrc_VLAs	.518	.168	9.477	1.679	.002											.601	.188	10.182	1.825	.001	.976	.267	13.333	2.654	.000
FIV5_ORDU_VLAs	.484	.174	7.756	1.623	.005						.393	.160	6.006	1.481	.014	.572	.198	8.326	1.772	.004	.990	.263	14.220	2.691	.000
FIV4_LTUsEU_VLAs	-.600	.184	10.649	.549	.001											-.588	.191	9.445	.555	.002	-.749	.232	10.442	.473	.001
FIV1_LTUsPU_VLAs	-.563	.178	10.047	.570	.002											-.637	.195	10.690	.529	.001	-.951	.236	16.201	.387	.000
FIV2_InatSrc_VLAs_X_FMV1_PILAs																					-.571	.249	5.254	.565	.022
FIV9_LocUniv_CLAs_X_FMV1_PILAs																					-.629	.272	5.334	.533	.021
FIV9_LocUniv_CLAs_X_FMV2_PrKn_PJ																					-.736	.281	6.852	.479	.009
FIV5_ORDU_VLAs_X_FMV4_PrExp_Wk_ORDU																					.505	.248	4.156	1.657	.041
FIV7_LTUs_CLAs_X_FMV4_PrExp_Wk_ORDU																					.714	.262	7.406	2.043	.006
FIV1_LTUsPU_VLAs_X_FMV5_PrKn_Core																					-.470	.264	3.177	.625	.075
FIV2_InatSrc_VLAs_X_FMV5_PrKn_Core																					.587	.264	4.941	1.799	.026
FIV3_LocUniv_VLAs_X_FMV8_PrExp_Wk_InatSrc																					-.586	.274	4.581	.557	.032
FIV9_LocUniv_CLAs_X_FMV8_PrExp_Wk_InatSrc																					.587	.305	3.696	1.798	.055
Cox&Snell R ²					.236					.115					.141					.338					.447
Nagelkerke ²					.329					.161					.197					.472					.625
Chi-square					55.922***					25.390***					31.553***					85.665***					123.321***
Percentage correct					79					73					74					81					86
No.					208					208					208					208					208
ΔCox&Snell R ²					-					-					0.026					0.223					0.332
ΔNagelkerke ²					-					-					0.036					0.311					0.464

Note:

- 1) In model 4, the three factors excluded before regression include a) FIV8_ORDU_CLAs and its interactions, b) FMV6_PrExp_Ed_LocUniv and its interactions, and c) FMV7_PrExp_Ed_InatSrc and its interactions, because they tend to have less power to predict output variables in all models.
- 2) Some variables with $p > .05$ are included in the regression because they still improve the prediction power of the model or do not meet the removal criterion of stepwise backward, see appendix C.3.

G.4 Regression Analysis for Mission-3--Criterion-2: Probability of Generating a Patent

Factors	1. Knowledge Inflow Baseline					2.1 Project Group Baseline					2.2 Intra-Organization Baseline					3. Integrated Model					4. Interaction Model				
	B	S.E.	Wald	Exp(B)	Sig.	B	S.E.	Wald	Exp(B)	Sig.	B	S.E.	Wald	Exp(B)	Sig.	B	S.E.	Wald	Exp(B)	Sig.	B	S.E.	Wald	Exp(B)	Sig.
(Constant)	-.520	.145	12.923	.594	.000	-.538	.148	13.239	.584	.000	-.546	.149	13.424	.579	.000	-.554	.150	13.541	.575	.000	-.695	.173	16.164	.499	.000
FMV3_PrExp_Wk_LTUs						-.391	.150	6.808	.676	.009	-.402	.152	6.974	.669	.008	-.406	.154	6.995	.666	.008	-.466	.180	6.725	.628	.010
FMV2_PrKn_PJ						-.267	.152	3.079	.766	.079	-.271	.153	3.136	.763	.077	-.274	.155	3.143	.760	.076	-.540	.191	8.009	.583	.005
FIV5_ORDU_VLAs																					.454	.186	5.984	1.575	.014
FIV1_LTUsPU_VLAs																					-.320	.181	3.111	.727	.078
FIV2_InatSrc_VLAs	-.259	.152	2.896	.772	.089											-.267	.154	2.985	.766	.084					
FIV5_ORDU_VLAs											.247	.147	2.837	1.281	.092	.250	.148	2.860	1.284	.091					
FIV4_LTUsEU_VLAs_X_FMV8_PrExp_Wk_InatSrc																					.475	.186	6.542	1.608	.011
FIV5_ORDU_VLAs_X_FMV3_PrExp_Wk_LTUs																					.452	.172	6.875	1.571	.009
FIV6_InatSrc_CLAs_X_FMV4_PrExp_Wk_ORDU																					.404	.204	3.911	1.497	.048
FIV5_ORDU_VLAs_X_FMV4_PrExp_Wk_ORDU																					.305	.181	2.854	1.357	.091
FIV5_ORDU_VLAs_X_FMV2_PrKn_PJ																					-.274	.170	2.601	.760	.107
FIV9_LocUniv_CLAs_X_FMV1_PILAs																					-.305	.175	3.058	.737	.080
FIV2_InatSrc_VLAs_X_FMV8_PrExp_Wk_InatSrc																					-.356	.191	3.485	.700	.062
FIV1_LTUsPU_VLAs_X_FMV5_PrKn_Core																					-.580	.219	7.035	.560	.008
FIV5_ORDU_VLAs_X_FMV5_PrKn_Core																					-.590	.236	6.284	.554	.012
Cox&Snell R ²					.015					.048					.061					.075					.237
Nagelkerke ²					.020					.065					.083					.102					.323
Chi-square					3.041					10.199**					13.044**					16.167**					56.182***
Percentage correct					62.5					65.9					63.9					63.9					72.1
No.					208					208					208					208					208
ΔCox&Snell R ²					-					-					.013					.027					.189
ΔNagelkerke ²					-					-					.018					.037					.258

Note:

- 1) In model 4, the three factors excluded before regression include a) FIV8_ORDU_CLAs and its interactions, b) FMV6_PrExp_Ed_LocUniv and its interactions, and c) FMV7_PrExp_Ed_InatSrc and its interactions, because they tend to have less power to predict output variables in all models.
- 2) Some variables with $p > .05$ are included in the regression because they still improve the prediction power of the model or do not meet the removal criterion of stepwise backward, see appendix C.3.
- 3) There are many variables with $p > .05$ in the regression. Also, in model 1, the Chi-Square is not significant at the level of $p < 0.05$. This observation suggests that generating a patent is not a strong function of knowledge inflows and is excluded from further analysis, see section 5.3.1.

G.5 Regression Analysis for Mission-3--Criterion-3: Versatility of Technology

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Factors	1. Knowledge Inflow Baseline					2.1 Project Group Baseline					2.2 Intra-Org. Baseline					3. Integrated Model					4. Interaction Model				
	B	S. E.	Beta	t	Sig.	B	S. E.	Beta	t	Sig.	B	S. E.	Beta	t	Sig.	B	S. E.	Beta	t	Sig.	B	S. E.	Beta	t	Sig.
(Constant)	3.240	.082		39.295	.000	3.240	.084		38.774	.000	3.240	.082		39.533	.000	3.240	.080		40.400	.000	3.240	.074		43.674	.000
FMV8_PrExp_Wk_InatSrc						.262	.084	.212	3.122	.002	.262	.082	.212	3.183	.002	.262	.080	.212	3.253	.001	.335	.077	.271	4.354	.000
FMV1_PILAs						.139	.084	.113	1.662	.098	.139	.082	.113	1.695	.092	.139	.080	.113	1.732	.085	.219	.079	.178	2.782	.006
FMV4_PrExp_Wk_ORDU																					-.168	.079	-.136	-2.124	.035
FIV2_InatSrc_VLAs	.208	.083	.168	2.515	.013											.208	.080	.168	2.586	.010	.215	.076	.174	2.820	.005
FIV5_ORDU_VLAs	.185	.083	.150	2.235	.027						.185	.082	.150	2.249	.026	.185	.080	.150	2.298	.023	.154	.076	.125	2.024	.044
FIV8_ORDU_CLAs	.185	.083	.149	2.233	.027						.184	.082	.149	2.246	.026	.184	.080	.149	2.295	.023					
FIV6_InatSrc_CLAs	.167	.083	.135	2.022	.044											.167	.080	.135	2.079	.039	.155	.077	.125	2.019	.045
FIV3_LocUniv_VLAs																					.145	.078	.117	1.865	.064
FIV1_LTUsPU_VLAs																					-.178	.078	-.144	-2.284	.023
FIV4_LTUsEU_VLAs_X_FMV1_PILAs																					.200	.080	.162	2.503	.013
FIV7_LTUs_CLAs_X_FMV1_PILAs																					.180	.079	.153	2.285	.023
FIV1_LTUsPU_VLAs_X_FMV2_PrKn_PJ																					.123	.071	.113	1.723	.086
FIV5_ORDU_VLAs_X_FMV2_PrKn_PJ																					.172	.081	.141	2.138	.034
FIV9_LocUniv_CLAs_X_FMV4_PrExp_Wk_ORDU																					.178	.087	.129	2.041	.043
FIV7_LTUs_CLAs_X_FMV2_PrKn_PJ																					-.234	.081	-.184	-2.895	.004
FIV6_InatSrc_CLAs_X_FMV1_PILAs																					-.212	.076	-.174	-2.771	.006
FIV7_LTUs_CLAs_X_FMV8_PrExp_Wk_InatSrc																					-.191	.081	-.149	-2.358	.019
FIV9_LocUniv_CLAs_X_FMV1_PILAs																					-.167	.077	-.139	-2.172	.031
R ²					.091					.058					.102					.149					.311
R ² adjust					.073					.048					.085					.123					.250
F					5.099**					6.256**					5.777***					5.857***					5.056***
No.					207					207					207					207					207
ΔR ² adjust					-					-					0.037					0.075					0.202

Note:

- 1) In model 4, the three factors excluded before regression include a) FIV8_ORDU_CLAs and its interactions, b) FMV6_PrExp_Ed_LocUniv and its interactions, and c) FMV7_PrExp_Ed_InatSrc and its interactions, because they tend to have less power to predict output variables in all models.
- 2) Some variables with $p > .05$ are included in the regression because they still improve the prediction power of the model or do not meet the removal criterion of stepwise backward, see appendix C.3.

G.6 Integrated Model of Knowledge Inflows and Internal Knowledge for Hypotheses 1 to 4

Factors	Model-Mission		3.Integrated Model 1: User Satisfaction					3.Integrated Model 2: Commercialization of Tech.					3.Integrated Model 3.1: Probability of Publication					3.Integrated Model 3.3 Versatility of Technology				
	Unstd.	Coeff.	Std. Coeff.				B	S.E.	Wald	Exp(B)	Sig.	B	S.E.	Wald	Exp(B)	Sig.	Unstd.	Coeff.	Std. Coeff.			
	B	S. E.	Beta	t	Sig.	B	S.E.	Wald	Exp(B)	Sig.	B	S.E.	Wald	Exp(B)	Sig.	B	S. E.	Beta	t	Sig.		
(Constant)	3.885	.073		53.116	.000	-.249	.215	1.343	.780	.246	-1.071	.203	27.809	.343	.000	3.240	.080		40.400	.000		
FMV1_PILAs	0.153	.073	.101	2.086	0.038											.139	.080	.113	1.732	.085		
FMV2_PrKn_PJ											.833	.203	16.883	2.300	.000							
FMV3_PrExp_Wk_LTUs	.366	.072	.246	5.088	.000	1.006	.216	21.624	2.736	.000												
FMV4_PrExp_Wk_ORDU						.509	.224	5.150	1.664	.023												
FMV5_PrKn_Core	.170	.073	.114	2.350	.020	.415	.204	4.161	1.515	.041	.446	.198	5.063	1.562	.024							
FMV6_PrExp_Ed_LocUniv	.178	.072	.119	2.464	.015																	
FMV7_PrExp_Ed_InatSrc																						
FMV8_PrExp_Wk_InatSrc											.416	.186	4.986	1.516	.026	.262	.080	.212	3.253	.001		
FIV1_LTUsPU_VLAs	.710	.072	.474	9.794	.000	1.820	.254	51.385	6.173	.000	-.637	.195	10.690	.529	.001							
FIV2_InatSrc_VLAs	-.127	.072	-.085	-1.766	.079						.601	.188	10.182	1.825	.001	.208	.080	.168	2.586	.010		
FIV3_LocUniv_VLAs											.713	.214	11.123	2.040	.001							
FIV4_LTUsEU_VLAs	.591	.072	.398	8.233	.000	1.072	.242	19.679	2.921	.000	-.588	.191	9.445	.555	.002							
FIV5_ORDU_VLAs						-.700	.226	9.597	.496	.002	.572	.198	8.326	1.772	.004	.185	.080	.150	2.298	.023		
FIV6_InatSrc_CLAs											.802	.217	13.645	2.231	.000	.167	.080	.135	2.079	.039		
FIV7_LTUs_CLAs	.513	.073	.340	7.023	.000	.435	.230	3.570	1.545	.059												
FIV8_ORDU_CLAs																.184	.080	.149	2.295	.023		
FIV9_LocUniv_CLAs	.159	.073	.105	2.177	.031																	
	R ²		.571			Cox&Snell R ²	0.485				Cox&Snell R ²	0.338				R ²		.149				
	R ² adjust		.550			Nagelkerke's R ²	0.648				Nagelkerke's R ²	0.472				R ² adjust		.123				
	F		27.175***			Chi-square	138.714***				Chi-square	85.665***				F		5.857***				
	No.		193			No.	208				No.	208				No.		207				
	?R ² adjust		0.491			?Cox&Snell R ²	0.383				?Cox&Snell R ²	0.223				?R ² adjust		0.075				
						?Nagelkerke's	0.512				?Nagelkerke's	0.311										

Note:

- 1) Some variables with $p > .05$ are included in the regression because they still improve the prediction power of the model or do not meet the removal criterion of stepwise backward, see appendix C.3.1)
- 2) Mission 3.2 (probability of generating a patent) is excluded from the analysis because is not a strong function of knowledge inflows, see section 5.3.1 and table 5.1.4.

G.7 Regression analysis for Interaction Model

Factors	Mission- 1: User Satisfaction					2: Commercialization of Tech.					3.1: Prob. of Publication					3.2: Prob. of Patent					3.3 Versatility of Technology					
	B	S.E.	Beta	t	Sig.	B	S.E.	Wald	Exp(B)	Sig.	B	S.E.	Wald	Exp(B)	Sig.	B	S.E.	Wald	Exp(B)	Sig.	B	S.E.	Beta	t	Sig.	
(Constant)	3.868	.063		61.145	.000	-.704	.357	3.882	.495	.049	-1.376	.269	26.224	.253	.000	-.695	.173	16.164	.499	.000	3.240	.074		43.674	.000	
FMV1_PILAs	.210	.066	.138	3.185	.002						.526	.254	4.276	1.692	.039	-.540	.191	8.009	.583	.005	.219	.079	.178	2.782	.006	
FMV2_PrKn_PJ																										
FMV3_PrExp_Wk_LTUs	.436	.066	.294	6.613	.000	1.627	.353	21.219	5.087	.000						-.466	.180	6.725	.628	.010						
FMV4_PrExp_Wk_ORDU											-.462	.271	2.908	.630	.088											
FMV5_PrKn_Core	.109	.065	.073	1.668	.097	1.985	.553	12.893	7.277	.000																
FMV6_PrExp_Ed_LocUniv																										
FMV7_PrExp_Ed_InatSrc																										
FMV8_PrExp_Wk_InatSr											.608	.237	6.588	1.836	.010							.335	.077	.271	4.354	.000
FIV1_LTUsPU_VLAs	.769	.065	.514	11.798	.000	3.996	.683	34.184	54.365	.000	-.951	.236	16.201	.387	.000	-.320	.181	3.111	.727	.078	-.178	.078	-.144	-2.284	.023	
FIV2_InatSrc_VLAs	-.167	.065	-.112	-2.559	.011						.976	.267	13.333	2.654	.000						.215	.076	.174	2.820	.005	
FIV3_LocUniv_VLAs											.527	.249	4.473	1.694	.034						.145	.078	.117	1.865	.064	
FIV4_LTUsEU_VLAs	.478	.065	.322	7.408	.000	2.731	.590	21.431	15.353	.000	-.749	.232	10.442	.473	.001											
FIV5_ORDU_VLAs						1.500	.381	15.521	.223	.000	.990	.263	14.220	2.691	.000	-.454	.186	5.984	1.575	.014	.154	.076	.125	2.024	.044	
FIV6_InatSrc_CLAs											.816	.256	10.174	2.262	.001						.155	.077	.125	2.019	.045	
FIV7_LTUs_CLAs	.480	.071	.318	6.738	.000	.907	.366	6.134	2.477	.013																
FIV8_ORDU_CLAs																										
FIV9_LocUniv_CLAs	.158	.065	.104	2.414	.017	1.019	.340	8.968	2.770	.003																
	R ²	.703				R ²	.604				R ²	0.447				Cox&Snell R ²	0.237				R ²	.311				
	R ² adjust	.665				Nagelkerke's R ²	.807				Nagelkerke's R ²	0.625				Nagelkerke's R ²	0.323				R ² adjust	.250				
	F	18.385***				Chi-square	192.909***				Chi-square	123.321***				Chi-square	56.182***				F	5.056***				
						% correct	92.3				% correct	86.1				% correct	72.1									
	No.	193				No.	208				No.	208				No.	208				No.	207				
	ΔR ² adjust	0.606				ΔCox&Snell R ²	0.502				ΔCox&Snell R ²	0.332				ΔCox&Snell R ²	0.166				ΔR ² adjust	0.209				
						ΔNagelkerke's R ²	0.671				ΔNagelkerke's R ²	0.464				ΔNagelkerke's R ²	0.226									

G.7 Regression analysis for Interaction Model (cont.)

Factors	Mission- 1: User Satisfaction					2: Commercialization of Tech.					3.1: Prob. of Publication					3.2: Prob. of Patent					3.3 Versatility of Technology				
	B	S.E.	Beta	t	Sig.	B	S.E.	Wald	Exp(B)	Sig.	B	S.E.	Wald	Exp(B)	Sig.	B	S.E.	Wald	Exp(B)	Sig.	B	S.E.	Beta	t	Sig.
FIV1_LTUsPU_VLAs_X_FMV3_PrExp_Wk_LTUs	-164	.067	-108	-2.440	.016																				
FIV1_LTUsPU_VLAs_X_FMV4_PrExp_Wk_ORDU	-151	.067	-101	-2.268	.025																				
FIV1_LTUsPU_VLAs_X_FMV8_PrExp_Wk_InatSrc																									
FIV4_LTUsEU_VLAs_X_FMV3_PrExp_Wk_LTUs	-155	.067	-108	-2.312	.022																				
FIV4_LTUsEU_VLAs_X_FMV4_PrExp_Wk_ORDU																									
FIV4_LTUsEU_VLAs_X_FMV8_PrExp_Wk_InatSrc	-144	.065	-097	-2.207	.029	.479	.299	2.566	1.614	.109						.475	.186	6.542	1.608	.011					
FIV7_LTUs_CLAs_X_FMV3_PrExp_Wk_LTUs						1.426	.378	14.220	4.160	.000															
FIV7_LTUs_CLAs_X_FMV4_PrExp_Wk_ORDU	-158	.065	-106	-2.437	.016						.714	.262	7.406	2.043	.006										
FIV7_LTUs_CLAs_X_FMV8_PrExp_Wk_InatSrc																									
FIV2_InatSrc_VLAs_X_FMV3_PrExp_Wk_LTUs																									
FIV2_InatSrc_VLAs_X_FMV4_PrExp_Wk_ORDU																									
FIV2_InatSrc_VLAs_X_FMV8_PrExp_Wk_InatSrc																									
FIV6_InatSrc_CLAs_X_FMV3_PrExp_Wk_LTUs																									
FIV6_InatSrc_CLAs_X_FMV4_PrExp_Wk_ORDU																									
FIV6_InatSrc_CLAs_X_FMV8_PrExp_Wk_InatSrc																									
FIV5_ORDU_VLAs_X_FMV1_PILAs	.125	.066	.083	1.881	.062																				
FIV8_ORDU_CLAs_X_FMV1_PILAs																									
FIV3_LocUniv_VLAs_X_FMV1_PILAs																									
FIV9_LocUniv_CLAs_X_FMV1_PILAs						.658	.341	3.718	1.930	.054															
FIV1_LTUsPU_VLAs_X_FMV1_PILAs																									
FIV4_LTUsEU_VLAs_X_FMV1_PILAs																									
FIV7_LTUs_CLAs_X_FMV1_PILAs	-149	.065	-104	-2.292	.023	-842	.375	5.043	431	.025															
FIV2_InatSrc_VLAs_X_FMV1_PILAs	-119	.065	-085	-1.835	.068	-750	.322	5.408	472	.020															
FIV6_InatSrc_CLAs_X_FMV1_PILAs																									

Note:

- 1) The three factors excluded before regression include a) FIV8_ORDU_CLAs and its interactions, b) FMV6_PrExp_Ed_LocUniv and its interactions, and c) FMV7_PrExp_Ed_InatSrc and its interactions, because they tend to have less power to predict output variables in all models.
- 2) Some variables with $p > .05$ are included in the regression because they still improve the prediction power of the model or do not meet the removal criterion of stepwise backward, see appendix C.3.