Report on Research at Harvard University, USA

How Learning by Using is Done: A Case Study on Laser Engraving Machines

by

Siegfried Sharma

Cambridge, June 2015

Acknowledgements

I want to take the opportunity to thank the Austrian Marshall Plan Foundation for this generous scholarship. This financial support was one of the factors that enabled me to conduct research at Harvard University, Cambridge, USA, to strive for “veritas”—to contribute to the field of innovation.

Thus, as shall be shown in this report, my doctoral thesis derived a great benefit from the Marshall Plan Scholarship, which was the making of great progress due to the collaboration with Prof. Stefan Thomke at the Harvard Business School and using Harvard University’s vast resources.

Table of Contents

(Page intentionally left blank)

Introduction

This report is aimed to provide the reader with a general idea of my research efforts at Harvard University, Cambridge, USA in the 2014/15 academic year. The reason for my stay at this institution, namely the Harvard Business School (HBS), was to work with Prof. Stefan Thomke on my doctoral thesis. He was the one to introduce me to the realm "Learning by Using" and, subsequently, the reason for my conducting this doctoral research.

Therefore, in this report I will present an extended summary of my thesis, its structure and content, which constitutes the progress of my work during this year at Harvard University. Every chapter will first be sketched out by its table of content, followed by an abstract of its subject matter. In this way, this research report should serve as a quick insight into the current state of my work, and the progress I made through the experiences I gathered in the year, subsidized by the Marshall Plan Foundation.

Though I would like to reveal as much of my research as possible at this point, I had to find a compromise between my own aspirations, the Marshall Plan Foundation report requirements, and constraints of circulation protection given the novelty of my research and findings.

Thus, I apologize that I cannot elaborate on details of my research in the depth that the interested reader might deserve and want to refer the ones who are keen to the final version of my doctoral thesis.

Part 1

Chapter I

Introduction

This Chapter shall provide the reader with an overall idea of my thesis and overview of my field of research.

In this thesis, I investigate the fundamentally simple question of the extent to which user activity on industrial machines and machine manufactures' development endeavor is determined through learning by using. Learning by using, a related kind of learning by doing, is external to the firm's manufacturers' production and development process, and can be considered a major innovation process activity. Though greatly underrated, "industries that rely heavily on learning by using—aircraft, electric power generation, telephones and, more recently, computers—have had some of the most impressive productivity growth in the twentieth century" (Rosenberg, 1982, p. 140).

To the best of my knowledge, after Rosenberg coined the term "learning by using" in 1982, with a study on maintenance progress in the aviation industry, not even a handful of papers have been directed towards this matter. However, what all the literature has in common is that it addresses the economic relevance of this phenomenon, although it is not aimed at understanding the ongoing processes at a micro-level. Thus, following Rosenberg's (1982, p. 140) encouragement, with this thesis, I will empirically examine the learning-by-using phenomena by more clearly identifying the nature and locus of the micro-level activities that provoke technological Ageations and will, therefore, contribute to the fields' understanding of technological change.

In detail, I will elucidate the learning-by-using process by means of a comprehensive study on users (operators) of industrial machines and the machines' manufacturer. More specifically, I aim to understand, why, how and under which circumstances users of industrial machines innovate, and how the manufacturer deals with the users' pieces of information (their problems and suggested solutions). To do so, I studied users, located in Germany, Austria, and Switzerland, of CNC laser machines produced by one manufacturer. As will be seen in my literature review, I sought to conduct this specific study for three reasons. First, although much prior work exists in adjacent fields, from which I draw my hypothesis, I know of no such study specifically addressed to the field of industrial machines. Second, industrial machines, as part of the manufacturing industry, are significant contributors to GDP. Therefore, considering their market share, to better understand underlying processes could reveal possibilities for improvements, and, consequently, could be of great financial potential—for individuals, firms, and social welfare.

Third, applications of CNC laser machines are widespread, through a range of sectors within the manufacturing industry. Hence, merging the results from my different case studies may result in more significant results than studying just one sector of this industry.

Based on my data, I will contribute to the field (of innovation) vis-a-vis how users learn to utilize industrial machines, and will reveal experimentation as the most important activity in this process. Subsequently, I will respond to the hypothesis of why and how users innovate, and will show two constraints of this process, which are new to the literature, viz. (1) limited access to resources (e.g. tools) and (2) the in individuals' (mainly operators) socialization process. Then, I will discuss why learning by using as it pertains to industrial machines is greatly underrated and, how tapping into this knowledge would contribute to manufacturers' R&D processes to help solve long-standing challenges in the design of new (versions of) products, accelerate the design development process and cut the associated time and expense. Summarizing my findings will show, that if manufacturers' consider users' information carefully, learning by using can be thought of as a process of real-world experimentation by the users in the manufacturers' product development scope and can generate such productivity improvements that products are utilized even beyond their initial (construed) performance characteristics. Thus, it can postpone the products' often premature advancement along a sustaining development curve, and a manufacturer's transition to a more sophisticated and smaller user group, where business, in the long run, may no longer be profitable (Christensen, 2005; Christensen and Bower, 1996).

Chapter II

Literature Review

In this chapter, I will review the body of literature directly related to my research. Despite having exhaustively ploughed through the broad range of literature on Product Development, Innovation, Learning, Problem Solving and Testing, it remains a work in progress. The reason is that I want to perfectly mesh the theoretical part of my research with my empirical studies, so that I can thoroughly deduce from theory to empiricism on the one hand and induce from empiricism to theory on the other. In this way, the reader will be provided with a holistic and gapless view on my research cogitations. Therefore I want to chart-like sketch my body of sources and refer the reader to my final thesis for more detail on this matter.

For my research, I want to define the following *terms*.

- *Manufacturers (M),* synonymous with *Producers (P)*: the provider of a design, product, or service that expects to benefit from its sales. Inventors creating knowledge to sell rather than use, shall be considered producers, as will those innovating to manufacture and sell goods embodying or complementing the original innovation.

- *User Firms (UF)*: organizations that expect to benefit from using the manufacturers' design, product, or service.

- *Users (U)*: the conglomerate of all users of a manufacturer's design, product, or service, statistically aggregated by a normal (Gaussian) distribution.

- *Ordinary Users (OU)*: the conglomerate of all users of a manufacturer's design, product or service, statistically aggregated between the lower Q(-SD) and upper Q(+SD) quantiles, i. e. two times the standard deviation ($\mu \pm$ SD), of the normal distribution with the users' applications versed-ness as the distinctive metric.

- *Innovative Users (IU)*: the conglomerate of all advanced users of a manufacturer's design, product or service, statistically aggregated by the upper quantile, Q(+SD), and *Lead Users (LU)* by the Q(+2*SD) quantile in the aforementioned normal distribution. Hence, this understanding is coherent with von Hippel's (1986) lead user notion, of lead users being ahead of the non-lead users with their applications, encountering additional requirements well before the rest of the user population.

- *Low-End User (LEU)*: the conglomerate of all users of a manufacturer's design, product, or service, statistically aggregated by the lower Q(-SD) quantile of the aforementioned normal distribution.

- *Non-Lead Users (OU)*: the conglomerate of all users of a manufacturer's design, product, or service, statistically aggregated below the Q(+2*SD) quantile of the normal distribution, and hence entailing IU, OU, and LEU.

As can be seen in the lead user definition, those sophisticated operators would benefit greatly from a solution to their requirements. The theoretical assumption is, that manufacturers face great (financial) uncertainty by addressing these niche-needs, and thus, lead users are being left behind to solve their issues on their own. To better understand the resulting users' innovative activity is why the body of literature on *innovation* shall be discussed in the following.

To the best of my knowledge, Smith (1937) was one of the first scholars to construe the field of user innovation with his findings that users innovate on their machines for ease of operation and productivity gains. These findings were followed by Enos (1962) with his work on the history of process innovation for petroleum progress and profits, who discovered, that almost all important innovations in this industry (for oil refining) stem from user firms. In 1976, Rosenberg presented his exhaustive study on the technological change in the machine tool industry from 1840 to 1910 to reveal the origins of some American technologies. He illustrated historical examples of technical convergence, like the transfer of innovation from bicycles to automobile makers or sewing machine manufacturing to firearms. Furthermore, based on my reading of the literature, his work is one of the first documents on user firms as innovators and producers of machine tools, which can be understood through a couple of examples from his research:

- the production of heavy machine tools for general purpose, which was first undertaken by textile machine shops, initiated by their internal industry requirements and those of the railroad industry
- the high-speed machine tools for more specialized applications, like milling machines or precision grinders, which literally stem from the production requirements of arms makers

- or, by the innovations of the Brown and Sharpe Manufacturing Company of Providence, Rhode Island, a clock, watch and mathematical device manufacturer, which was a unique tool contributor too, as a consequence of their demands in sewing-machine operation.

To summarize, he found out that “the results of these efforts were machine tools of a general usefulness far surpassing the industry of origin.”(Rosenberg, 1976, p. 22). At around the same time, von Hippel (1976) illustrated in his paper, that users of four different types of scientific instruments (gas chromatography, nuclear magnetic resonance spectrometry, ultraviolet absorption spectophotometry, and transmission electron microscopy) can be ascribed the significant innovations in this industry. Von Hippel (1977) could confirm these findings for the semiconductor industry in a study on innovations in process machinery for semiconductors and electronic subassemblies. Moreover he could show that the users dominated the entire innovation process, from need recognition to building and using the prototypes in their commercial production. Pavitt (1984) complemented these findings with a study on significant innovations in Britain from 1945 onwards, and extended the dimensions of innovative activity by another source of knowledge external to the manufacturer—production intensive, science based—supplier innovations. His other classified categories—are not new to the field, but reinforce the findings at other places for the European or, at least, the British context.

More interestingly, and to close the arc of the aforementioned manufacturers' uncertainty in addressing lead user niches, scholars demonstrated that many of the commercially most significant and novel products in a range of fields are rather developed by users than manufacturers (Enos, 1962; Freeman et al., 1968; Knight, 1963; Shaw, 1985; von Hippel, 1988)[1]. Further studies (Baldwin et al., 2006; Franke et al., 2006; Franke and von Hippel, 2003) confirm the bulk of research, especially regarding lead user innovation.

Yet, in none of the aforementioned pieces could I find any indication on research on the micro-level mechanisms of (industrial machine) user

[1] On a complementary note, Shah (2000) eked the land of user innovation beyond the industrial context to consumer goods and a sports-related one. She extended the terminology by the user-manufacturer innovation, and could show that all first of type innovations were solely developed by users and that user-manufacturers were responsible for a bulk of the "improvement innovations".

innovation activity, though some literature might have touched hypothetically on certain aspects such as when users innovate. The only attempt to understand inventive activities more in-depth appears to have been made by von Hippel and Tyre (1995) via a study of problems encountered in the first years of novel process machines. However, central to this exploration is providing a more comprehensive understanding of the learning behaviors in problem-solving and its influence on the learning curve.

An excurse into *problem-solving* shows that a problem can be considered an “unsatisfied need to change a perceived present situation to a perceived desired situation” and can be regarded solved when the “perceived present and desired situations are perceived to be the same” (Bartee, 1973, p. 439). This process—the problem- to the solution-state change—is generally understood as problem-solving and can be achieved in three ways (Bartee, 1973). Literature in product and process development (Alexander, 1964; Clark, 1991; Iansiti, 1998; Wheelwright, 1992) unfolds a towards an envisaged solution-directed trial and error measure (Allen, 1966; Baron, 2000; Marples, 1961; Smith and Eppinger,

1997) fundamental to problem-solving and, thus to experimentation, which can be considered a form of problem-solving (Duncker, 1945; Marples, 1961; Simon, 1996; Thomke et al., 1998; Thomke, 1998). However, since the body of literature shall be tailored in strong conjunction with the explorative findings in my final thesis, and problem-solving shall be further understood from a process of learning, I want to pivot the discourse towards the scope of learning.

In general, *learning* can be considered as an iterative action and reflection process, in which actions are assessed and modified by actors towards desired outcomes (Dewey, 1938; Edmondson, 2002; Kolb, 1984; Schön, 1983). In case the actors are organizations, drawn from behavioral science, the learning process can be understood as “encoding inferences from history into routines that guide behavior” (Levitt and March, 1988, p. 320). In other words, target oriented learning actions of organizations, especially into new product design, tend to rely on history rather than on anticipations of the future (Cyert, 1963; Levitt and March, 1988; Lindblom, 1959; Nelson, 1982; Siegel, 1957; Simon, 1996; Steinbruner, 1974) and are discussed in two forms in the bulk of learning literature—

(1) organizational search (incl. traditional marketing research methods) and (2) trial-and-error experimentation. Most past research was on the latter, in detail, learning by doing and consequently different variables of influence and forms of the learning curve. With my thesis I shall show that Rosenberg's (1982) supplementation of this—roughly speaking—twofold organizational focus by a third, external factor, the learning of user (firms), was in fact appropriate and deserves further attention. Therefore, in the following I will expose the "vast sea of literature", to better demonstrate where my thesis anchors in the respective field.

One of the scholarly pioneers to explore the decrease in labor-production costs over units produced can be considered (Wright, 1936) with his study on factors affecting the cost of airplanes. His cornerstone work opened an entire field of research, with a great amount of literature, resulting in the study of this so-called learning curve principle—functions that are used henceforth, to delineate labor learning, learning by doing, at a meso-level (production process). The literature ploughed the learning curve in a descriptive and explanatory way. The descriptive depiction ranges from discussions (1) of the learning curve graphs' variables (Alchian, 1959; Arrow, 1962; Cooper and Charnes, 1954; David, 1970, 1970; Fellner, 1969; Rapping, 1965; Stobaugh and Townsend, 1975), and (2) the functional form of the learning curve (A. Garg, 1961; Asher, 1956a; Baloff, 1971, 1966a, 1966b; Carlson, 1973; Carr, 1946; Conway, 1969), to (3) differences in learning rates (Alchian, 1959; Asher, 1956; Hirsch, 1952; Stobaugh and Townsend, 1975). The explanatory discourse, which I consider most fruitfully characterized in direct (Andress, 1954; Hartley, 1965; Hirschmann, 1964) and indirect labor (Hirschmann, 1964; Hirsch, 1952), tries to explain the learning curves' underlying effects. The direct labor studies are focusing (4) on the influence of (minor and major) technical changes (Hollander, 1965), (5) learning effects in equipment modifications (Arrow, 1962; Searle and Goody, 1945; Sheshinski, 1967), and (6) capital intense activities (Baloff, 1966a; Hirschmann, 1964; Hirsch, 1952). The latter is where indirect labor literature can be found as well.

Another segment of learning curve research is focused on the behavioral factors in the scope of the learning process. Hollander (1965) revealed these sources of increased efficiency with a study of du Pont rayon plants, whereas Baloff (1970) suggested labor motivation and technical support as influential variables, and HaYes (1984) discussed factors encouraging and impeding learning. However, what all these studies have in common is that they did not model the presented factors as a mathematical curve, unlike Levy (1965). He introduced an adaption function to model how firms adapt to and improve their performance by characterizing the behavioral factors into (pre-) planned or induced, industrial engineering (or exogenous), and autonomous learning, attributed to on-the-job learning or training, which was complemented by Dutton and Thomas (1982) through cross-tabulating different forms of distinctions.

Wright's (1936) cornerstone piece also resulted in curves of improvement types and analysis units different from the learning curve, viz, the progress and experience functions. Progress curves (Dutton and Thomas, 1982; Gold, 1981; Henderson, 1971), enunciated in unit costs, "may describe changes in material inputs, process or product technologies, or managerial technologies—from the level of a process to the level of a firm" (Dutton and Thomas, 1984, p. 235), and, therefore, under my considerations from a meso-to-macro perspective. Experience functions (cf. Alchian, 1963; Billon, 1966; Nadler and Smith, 1963) in contrast often describe progress at an industry level with price as the proxy (Dutton and Thomas, 1984), though they are often used interchangeably with learning curves (Pisano et al., 2001).

However, aside from Adler's and Clark's (1991) approach to sketch the learning process, this summary of the body of literature should have shown that research on understanding the micro-level learning processes behind the learning curve is very thin—especially w.r.t. how learning by using is done.

Chapter III

Methodology of Overall Research: Research Design

In this chapter, I will reveal and discuss my general methodological approach to the research question. For my explorations, I chose to select all of the study samples from the universe of one manufacturer of CNC laser machines. I focused on the users of these machines in the German-speaking area, their interaction with the machine-system compound (such as the machine itself, the exhaust system and the software) in their work environment. Three different scenarios of the machines' field of operation will be generalized: (1) one-man businesses with order-related pieces (unique copies) and small batch productions, (2) medium-size businesses with order-related pieces (unique copies) and serial productions, and (3) large firms with serial productions only and, where the laser machines are just one of several machines in the production cycle. In the section of the CNC laser machine description, I will show that these machines were not chosen randomly but rather for the following two reasons: (1) CNC lasers have a broad area of application within the entire manufacturing sector and, therefore, I anticipate the research findings to be generalizable for the manufacturing industry. (2) All the examined, different models of CNC laser machines share the same (relatively trivial) technology and interfaces, which is why I consider them a good fit for comparable studies. Then, in the *Overall Study Design* section, I will emphasize the explanation of my triangulated research composition, which I composed out of different qualitative and quantitative research methodologies—from open to fully structured forms. I clustered these methodologies in the following four sequential steps (illustrated in figure III.1):

(1) A *Preliminary Field Study*, by blending a literature research, ethnographical expert interviews as well as field data from the manufacturer's service engineers, which I applied for my first orientation and learning the ropes in the field;

(2) A *First Field Study*, by triangulating a questionnaire with workflow analyses, to gather the users' assessments of their work systems—the machine environment compound—as well as their demographics in such a way that the standardized responses could be correlated and dependencies of the variables discerned;

(3) A *Second Field Study*, consisting of narrative focus group discussions, aimed towards an understanding of the first field study's findings, the users systems of relevance and their latent (tacit) knowledge;

(4) A *Third Field Study*, comprising a lead user study with open, (funnel-) guideline-oriented, face-to-face interviews and, fully structured telephone interviews with the manufacturer's R&D director, built upon my prior studies' results and implemented, to draw my overall research conclusions from above—with an overview onto both, the users' and the manufacturer's activities.

Hence, in total, seven different data collection methods[2] were carefully elected and adapted, given that the aim of my studies is to understand, why, how and under which circumstances users of industrial machines innovate, and how the machine developer deals with the users' pieces of information (their problems and suggested solutions). I will conclude this chapter by outlining chapters IV to VII.

[2] Of which I newly conceived two for my research, as the commonly used methods would have not served the specific research questions to my satisfaction.

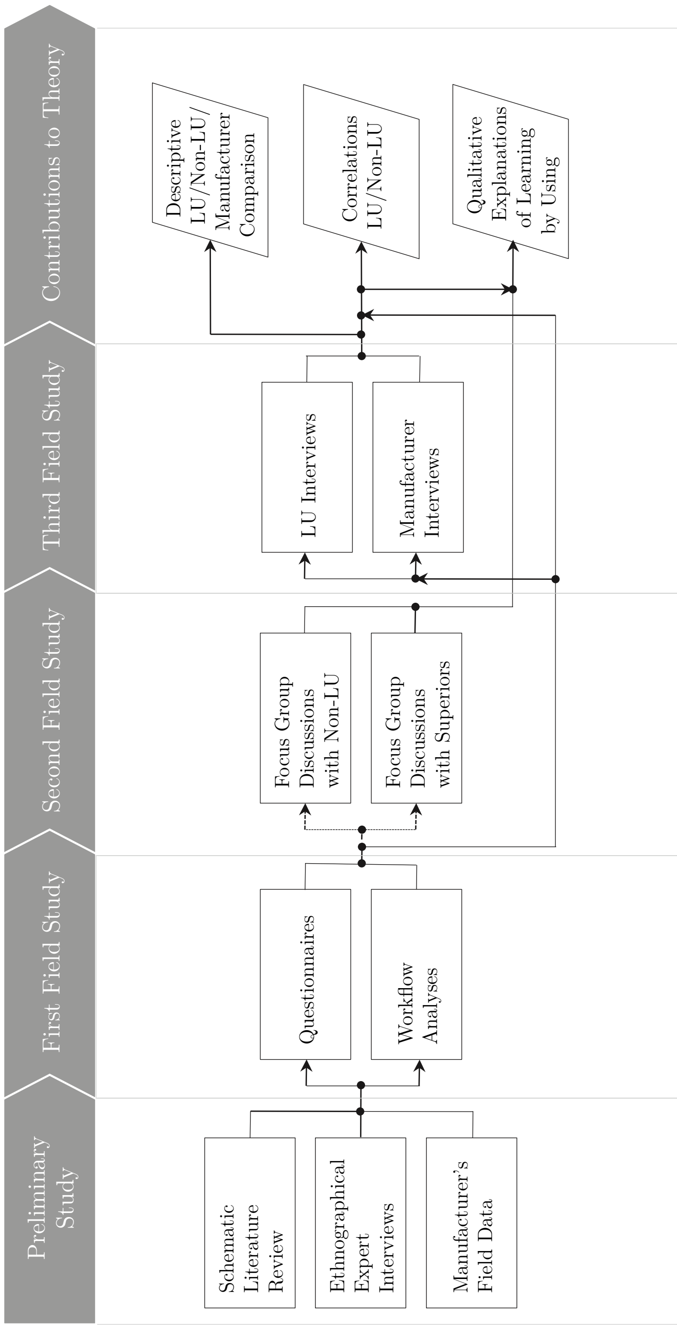

Figure III.1. Research design and flow of information.

(Page intentionally left blank)

Part 2

Chapter IV

Preliminary Study: Getting into the field of Innovation through Expert Interviews and Data from Manufacturer's Service Engineers

"Since *research results are strongly a function of definitions, sample selection criteria, and data collection methodology*" (von Hippel, 1977, p. 60), I conducted a preliminary study to lay solid foundations for my research work to follow.

This preliminary study served for my first orientation in the field, and, hence, to acquire a better understanding of the users' perspective, their contextual language and the thereby conveyed associated knowledge. To understand the shared context of the users' everyday communication, I conceived a new interview form by merging ethnographical studies with expert interviews. Only through my own experience of working together with users (the experts on the machines) in their environment, could I establish a common ground with them and, therefore, create shared knowledge and language, which I considered to be essential for my research.

Therefore, I spent one day working together with two users in a medium-sized company solving problems they encountered during the typical workday and digging deeper into my own understanding by scrutinizing their actions.

My findings comprised the first draft of hardware and software dimensions for the questionnaire of my first field study, and were complemented by data attained by the manufacturer's service engineers.

As a researcher, being an exogenous factor to the user and their environment would entail the risk of bias of constrained data, which had to be avoided through thorough consideration. The latter will be discussed in the section *Bias in Findings*, whereas the section *Discussion Within the Greater Context* of my research will entail a conversation about the further exploitation of the preliminary's studies yielding. Finally, this chapter will be concluded with the key takeaway of this research step and its meaning for the scientific community.

Chapter V

First Field Study: Questionnaire and Workflow Analysis

My first field study consists of a triangulation of (1) quantitative and (2) qualitative research methods.

(1) In my *quantitative approach*, questionnaires were applied for methodical and formal reasons. Methodical justification is provided as this method can represent quantities of attributes of the objects measured and gather representative scores and dependencies of the users

on the formed attributes, without exertion. Furthermore, what should be capitalized on, by applying questionnaires, is the ability to gather responses in a standardized way from a large and widely scattered sample size, which is the most important formal reason.

I implemented a questionnaire on sociodemographic, job satisfaction, ergonomic and technical-aspects within the research boundaries, addressed to a target sample size of 103 users at 38 firms in Austria, Germany and Switzerland. A response rate of 45,6% (47 users) was achieved. Items with a relative frequency of negative scores above 7% in the responses were identified as *problem fields* and the ones related were clustered into *overall problem fields*. In sum 32 problem fields were encountered and summarized in 11 overall problem fields. In a further analysis, the problem fields were correlated—Chi-Square, Fisher's Exact-, and Mann Whitney U-tests for independency and dependency of variables, Kolmogorov-Smirnov tests to test for normal distribution—on the one hand with labor system elements, and on the other hand with socio-demographic data.

As a result, most noticeable is that experimentation is the significant factor for learning to operate the machines properly/to full extent. Furthermore, in terms of learning by using interesting to note is that age is a significant factor for how users were trained to operate the machines.

The bias discussion should draw on the fact of constraints in research, and how this high response rate, despite limited monetary incentives, could be due to my appeal to the users' intrinsic motivations— i.e to improve their everyday work.

(2) As for the *qualitative approach* in this study, workflow analyses were applied to observe the field under non-laboratory state, thus, real-life conditions, mainly to spot deficiencies, which are subconscious to the users and, therefore not measured with the questionnaire.

The workflow analysis was implemented in two ways. First, a section in the questionnaire would address the user's individual workflows. Second, 8 users of the machines were observed while manufacturing with the CNC lasers.

Transcription of the observed data, its content analysis and description resulted in that all studied users undertook the workflows in the same way (sequence and steps). Furthermore, 5 *overall problem fields* during the workflow were observed, which reinforced the questionnaire results, showing that experimentation is in particular the most important factor to better know the machine functions.

Additionally, I will consider how these questionnaires will be used in the further context of my research. The bias discussion for the workflow analysis will encompass the influence of recording techniques as disruptive factors in the data collection in the natural environment of the users and how this bias was avoided by the measurement settings.

Finally, in the conclusion section, merging of the questionnaires and workflow analyses will be subject of discussion. Furthermore, a brief outlook shall be given on how this study will be used in my further research.

Chapter VI

Second Field Study: Narrative Focus Group Discussions

My second field study draws upon the qualitative methodology of narrative focus group discussions. The narrative focus group is a form of group discussion technique, which I newly developed by merging the narrative inquiry technique with group discussions. The term “focus” in the name may indicate that the discussion is kept within a certain topic-range, which is only triggered by the moderator’s input at the start of the discussion. Therefore, by means of the participants’ narration and their consequent argumentation/negotiation of knowledge[3] with the other discussants, they would reveal increasingly more tacit information with advancement of the discourse, and, thus, point towards their latent constructs.

This new technique was applied for multiple methodological reasons. It was used to gather a more comprehensive and deeper understanding of the users interaction with the machines, and to further narrow the problem definition. In this sense, the group discussions were applied as a corrective to the questionnaire, as the latter's standardized questions and items capture the range of variety of attitudes only insufficiently. Therefore, my aim for the data collection with this tool was to recall the users' collective memory of everyday work life in order to better understand their (shared or different) common ground of perspectives—from their socialization-processes onwards to operating the machines, up to their (physical and social) work environment.

Three group discussions were conducted, two of them with ordinary users and the other with work superiors. An investigator triangulated content

[3] With argumentation/negotiation, in lieu of the process of reaching an agreement, the process of coming to a mutual understanding on a matter is meant in this case.

analysis of the discussion content with a Guetzkow's U agreement for intercoder reliability, resulted in 2139 units for the female, and 3025 units for the male non-lead users, and 2975 units for group of work superiors.

Among all groups, 71 discussion topics (categories) could be found. A frequency analysis revealed a rank of the most dominant topics for the individual discussions:

For the *group of female non-lead users*, Field of Application (24.18%), Functional criteria (10.94%), and Load in material (6.65%) were the predominant topics;

For the *group of male non-lead users*, Field of Application (14.27%), Training Requirements (7.66%), and Learning by Doing / Trial and Error (5.51%) were the predominant topics;

For the *group of work superiors (lead users)*, Accessories (12.27%), Field of Application (11.83%), Learn to Use the System / Training (6.817%), the predominant topics;

Though the results between the groups might appear similar at a first glance, the content differs strongly within the categories. While, for example, most of the Field of Application units of the female discussion group expressed their problems with processing unique pieces and other applications, the group of work superiors mostly exchanged information about how to best extend their scope of applications with the most suitable innovation. However, a detailed explanation of the categories, their contents within the individual groups, a group comparison and a sequence analysis will be depicted in my thesis. Moreover, I will list the innovations that were expressed within the groups and will discuss their relevance.

In the discussion section of this chapter, I will then address the bias of the methodology. In general, the flanks of group discussions' research settings are wide open and particularly susceptible for biases and, therefore, these factors of influence, which are roughly speaking the group composition, spatiotemporal aspects, and the moderation, have to be considered in reference to the research question and intended aim of study.

Finally, the import of my findings in the scope of my research shall be contemplated by merging the discoveries with those of my prior studies. I will discuss the innovative activities and topics of the group of work superiors and draw the arc to lead user behavior. Moreover, a brief outlook will be given on how these results will be further processed in the context of my study to follow.

Chapter VII

Third Field Study: Interviews with Lead Users (LU) and Manufacturer

My third study exploration harvests the field of qualitative research for suitable measuring instruments, which we[4] concluded to be (1) lead user studies and (2) interviews with the manufacturer's R&D department.

Methodical reasoning is given, as lead users and ordinary users may not only solve problems differently, but may further encounter different types of problems. Therefore, the lead users needed to be examined separately

---

[4] In recognition of Prof. Stefan Thomke's suggestion during one of our meetings.

with an open methodology. The telephone interviews with the manufacturer's director of R&D, were a consequence of spatiotemporal factors and the urge to attain comprehensive and first-hand information about the producer's line of decision processes.

(1) The implementation of the *lead user study* involved pyramiding (cf. von Hippel et al., 1999), with the manufacturer's user database and their service engineers' recommendations for innovative user firms, as my starting point. My systematic search yielded in 5 lead user interviews, which I kept open in the first part of every conversation and then expanded into a structured poll on the problem fields the ordinary users experienced. A summarizing content analysis clustered the raw material into 18 inductive and deductive categories and concluded 199 units, of which 101 (50.8%) were initially problems, and 98 (49.2%) initially non-problems. Of these initial problems, 71 (78.2%) could be solved to the lead users' full satisfaction, remaining in 22 (21.8%) insufficient addressed issues.

Overall, 116 units were counted for lead users approaches to challenges they encounter while working on the machines. In 26 (22.41%) cases, the users innovated by *modifying the machines*, in 32 (27.6%) instances, by *process changes*, whereas in 2 (1.7%) times, *material innovations* lead to a sufficient problem solution. Furthermore, the content analysis exposed 12 (10.3%) units, which were problems ordinary users encountered and the lead users could envisage but did not experience, as they had solved them from the *outset*. In 10 (8.62%) cases, the lead user made solution proposals, as they could not apply those themselves, because the closed machine architecture would not provide users with the opportunity to do so. In one instance, the user did not want to intrude on the existing system too severely. 30(25.9%) times, *user adjustments* were necessary to deal with the situation, as a solution would not be feasible or conceivable to the users. These cases included user adjustments through learning by doing and adjustments *to bugs*, acceptance of certain (not changeable) *work conditions* like the odor emission while processing specific materials or the acceptance of *technical aspects* the manufacturer could not avoid. However, only in a few instances, viz. 4 (3.44%), users were not able to find any of those aforementioned approaches to deal with the situation.

One might now wonder about the differences in the sums of solved and unsolved problems. The reason for this is twofold. First, though the users might have addressed an issue, it does not necessarily mean that the problem is fully solved. For example, in most of the cases, an adjustment to a problem meant that users couldn't solve it in another way, and, therefore, had to adjust their own behavior to the issue. Second, it is also a consequence of how the units were utilized. The reference point for my interpretation was the users' solution approach, meaning that if the interviewees were using multiple ways to address the same problem, all of them were further analyzed. Conversely, if one innovation served to solve various problems just this one was interpreted.

(2) After understanding the lead users' problems, the *manufacturer interviews* were conducted. Three telephone interviews, in total 4.5 hours, were necessary to capture all the required information, to compare the elicited data with the lead user data set. Interestingly, the manufacturer was aware of almost all the users' problems (97.5%), but contributed only with 3 "innovations" (5%) to the applied solution-space. This sharp contrast can be reasoned with means of my data, as a loss of

information in the user-manufacturer knowledge-transfer process, and hypothesis derived from literature.

Beyond this bias discussion, I want to reflect on my findings within the field of innovation. In other words, I will compound the innovations, deduced from the group discussions with work superiors (from chapter VI) with those from this field study. Then, I will discuss this conglomerate on innovations with the body of literature on (empirical studies on) user innovation cf. Abernathy, 1976; Coleman, 1966; Enos, 2002, 1962; University of Sussex. Science Policy Research Unit, 1972; von Hippel, 1977; von Hippel and Finkelstein, 1979, von Hippel et al., 1999;), to understand effects specific to the context of the manufacturing industry as well as draw conclusions for phenomena that might be experienced throughout different fields, and hence, contribute to the theory of innovation.

Chapter VIII

Summary and Correlation of Field Data

This chapter should summarize my gathered research data and show the results of its subsequent correlation. Though showing all of my data would exceed the constraints of the page and word limit of this report and, further, would be in contradiction to the circulation protection of my work, I still wish to show some evidence for the sake of transparency. Furthermore, developing the tool to measure relevant lead user attributes for the comparison with non-lead users, gathering the data, analyzing and interpreting it, reflects the bulk of my work at Harvard University and thus, space will be devoted to showing some of the most important ones.

In the following (Table VIII.1), I will provide an overview with important items, which were cross tabulated for the lead and non-lead user comparison. For circulation protection reasons, a description of these variables will be provided in my final thesis only. Then, in Chapter IX, these correlation results, of the items I consider most relevant for this report, will be represented with Crosstabs, Chi-Square Tests, Directional Measures, and Symmetric Measures.

Crosstabs will show the (standard (std.) and adjusted Residuals, the observed and expected count to enable insight into the direction of the dependencies. The Chi-Square Tests show the resulting P-values which were consequently tested against chosen alpha errors. The Directional and Symmetric Measures show the strength of the correlations. Values of $0 < r < 0.2$ reflect a very low correlation, $0.2 < r <= 0.5$ a low correlation, $0.5 < r <= 0.7$ an average correlation, $0.7 < r <= 0.9$ a high correlation, and $0.9 < r <= 1$ a very high correlation.

Table VIII.1. Case Processing Summary of Correlated Items

Correlated Variables	Description of the Variables
Years of Work on Laser Systems * User	Description will be provided in the final thesis
Weekly Hours of Work on Manufacturer's Machines * User	
Years of Computers Usage Before Laser Systems * User	
Need for Training * User	
Right or Left Handedness * User	
Sex * User	
Age * User	
First Language * User	
Migration * User	
Highest Completed Educational Attainment * User	
Technical Training /Engineering Apprenticeship * User	
Material Positionability * User	

Correlated Variables	Description of the Variables
Workpiece Reachability * User	Description will be provided in the final thesis
Laser Movement Speed * User	
Table Movement Speed * User	
Table Positioning Accuracy * User	
Cutting- and Engraving-Quality * User	
Material Positioning Accuracy * User	
Machine Noise Level * User	
Dust Exposure and Odor Pollution * User	
Distances of the Keys from Each Other * User	
Key Size * User	
Number of Functions * User	
Function Intuitiveness * User	

Correlated Variables	Description of the Variables
Menu Architecture * User	Description will be provided in the final thesis
Free-Handed Operability * User	
Laser Beam Focusing Problems * User	
Load-in Material * User	
Unload Material * User	
Engraving Table Change * User	
Vacuum Table Change * User	
Cutting Table Change * User	
Honeycomb Table Change * User	
Cleaning of the Machine's Working Area * User	
Exhaust System Maintenance * User	
Vector Ordering * User	

Correlated Variables	Description of the Variables
Software Logic * User	Description will be provided in the final thesis
Menu Architecture Logic* User	
Submenu Logic * User	
Submenu Plate Setup Logic * User	
Legibility of the Symbols * User	
Self-Explanatory Symbols * User	
User Interface Customizability * User	
Years of Work on Laser Systems * User	
Weekly Hours of Work on Manufacturer's Machines * User	
Years of Computers Usage Before Laser Systems * User	

(Page intentionally left blank)

Part 3

Chapter IX

Merging the Field Studies: LU and Non-LU Comparison

In this chapter, I will merge the aforementioned described field studies and will draw my conclusion on a comparison of lead users and non-lead users. Not content to merely descriptively illustrate my data, statistical testing should inject excitement into this part of my research.

In order to triangulate my methodologies, I used my first field study's questionnaires as a base for my data analysis and coded my qualitative data of the third field study's lead user interviews into this quantitative data set of non-lead users. In other words, I assigned the content analyzed lead user responses to the respective questionnaire items of my first field study in two ways[5]. First, I correlated the non-lead user responses with the lead users' initial assessments, i.e before they have solved or adjusted to the problems they encountered. Second, I correlated the non-lead user responses with the lead users' final assessments, i.e after they have solved or adjusted to the problems they encountered.

My hypothesis for these correlations was raised by my literature and empirical findings. As non-lead users' innovative/modifying activity is significantly weaker than those of the lead users (von Hippel, 2005), I will assume that if any, there are only very little differences of the non-lead users initial and final assessments. This can be supported by my following findings: (1) Form my third field study I know that most of the

[5] One might argue, that with an anonymous questionnaire, sent out to the entire user population in the German-speaking area, I might have also had lead users in this dataset without being aware of it. However, I controlled the data, and filtered out the one encountered lead user. The data presented in Chapter VIII is not adjusted by this user. However, more on this shall be discussed hereafter, in the bias section.

users inventive activity is directed towards problem solving (of challenges encountered in their work day). (2) From my second field study I know that, in general, non-lead users deal with problems by their own adjustments to them. (3) From my first and my second field study I know that, after years of working with the machines, non-lead users mainly encounter the same problems as they did from the outset. Therefore, I hypothesize, that the non-lead users' assessments do not (significantly) differ over the time, and consider them as a constant with non-LU_{inital} (t = 0) assessment = non-LU_{final} (t = date of survey) assessment = non-LU assessment—the latter term is, which I will only refer to in the following.

My hypothesis for these correlations was raised by my literature and empirical findings. As non-lead users' innovative/modifying activity is significantly weaker than those of the lead users (von Hippel, 2005), I will assume that if any, there are only very little differences of the non-lead users initial and final assessments. This can be supported by my following findings: (1) Form my third field study I know that most of the users inventive activity is directed towards problem solving (of challenges encountered in their work day). (2) From my second field study I know that, in general, non-lead users deal with problems by their own adjustments to them. (3) From my first and my second field study I know that, after years of working with the machines, non-lead users mainly encounter the same problems as they did from the outset. Therefore, I hypothesize, that the non-lead users' assessments do not (significantly) differ over the time, and consider them as a constant with non-LU_{inital} (t = 0) assessment = non-LU_{final} (t = date of survey) assessment = non-LU assessment. In the following, I will only refer to the latter term.

As for the questionnaire items, a (non-median split) dichotomizing of the variables—into “problem” / “no problem” encountered—was necessary, as my qualitative interviews (out of time constraints) only allowed closed questions for its structured portions. However, Fisher's Exact and Mann-Whitney U tests were applied to correlate non- and lead users' problem fields and proof the resulting P-value against an alpha error of 5%. Since the dichotomizing of the variables may result in a loss of test power (1-beta), the level of significance may be increased to enhance the test's power. Which means, that the exact P-values[6] of even low significance (for alpha errors up to 10%) will be stated for the interested reader, as they might be an indication for a link between the correlated variables. Furthermore, Spearman's rho, Rankings, and Residues were calculated to interpret the strength and direction of the correlations. In the following, I offer a quick outlook on what my data shows, first in a descriptive way and afterwards for the correlations.

In general, descriptively depicted, lead users reported fewer problems than non-lead users. However, in cases where they did not, the biggest deviating results between lead and ordinary users could be found in the material positioning accuracy, the material positionability, and the self descriptiveness of the software symbols—for which each of these problems, lead users reported 56% more dissatisfaction. Further, lead users reported more problems in vector ordering (45%), in changing the honeycomb table (32%), in their intuition of the control panel functions (25%), and in the distances of the keys to each other (13%), among other minor differences.

[6] As a side note, in the final version of my thesis, the correlation coefficient and its significance level only will be addressed, as instead to the exact P-values like in this outline.

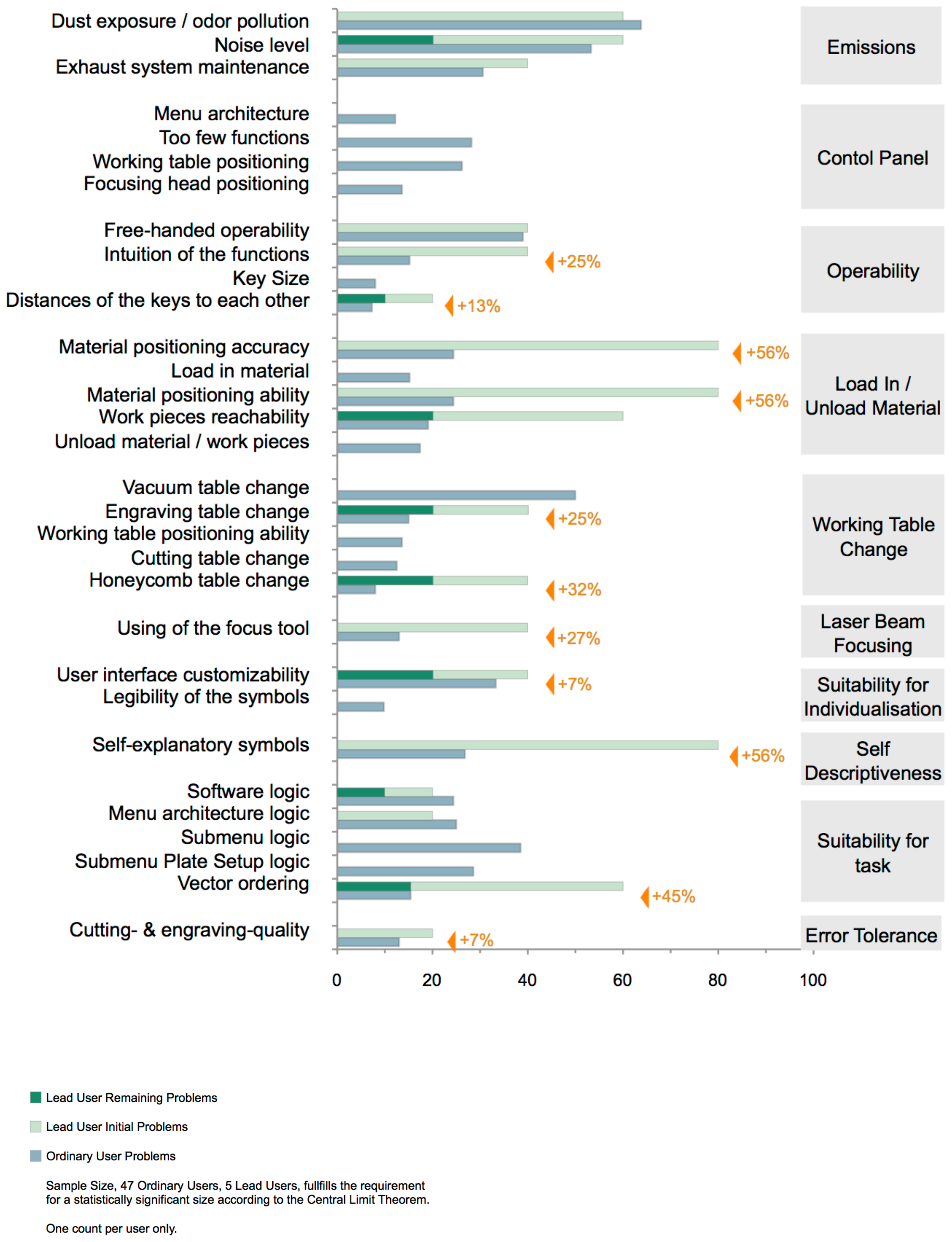

Figure IX.1. Problem Areas of Ordinary Users and Lead Users in %

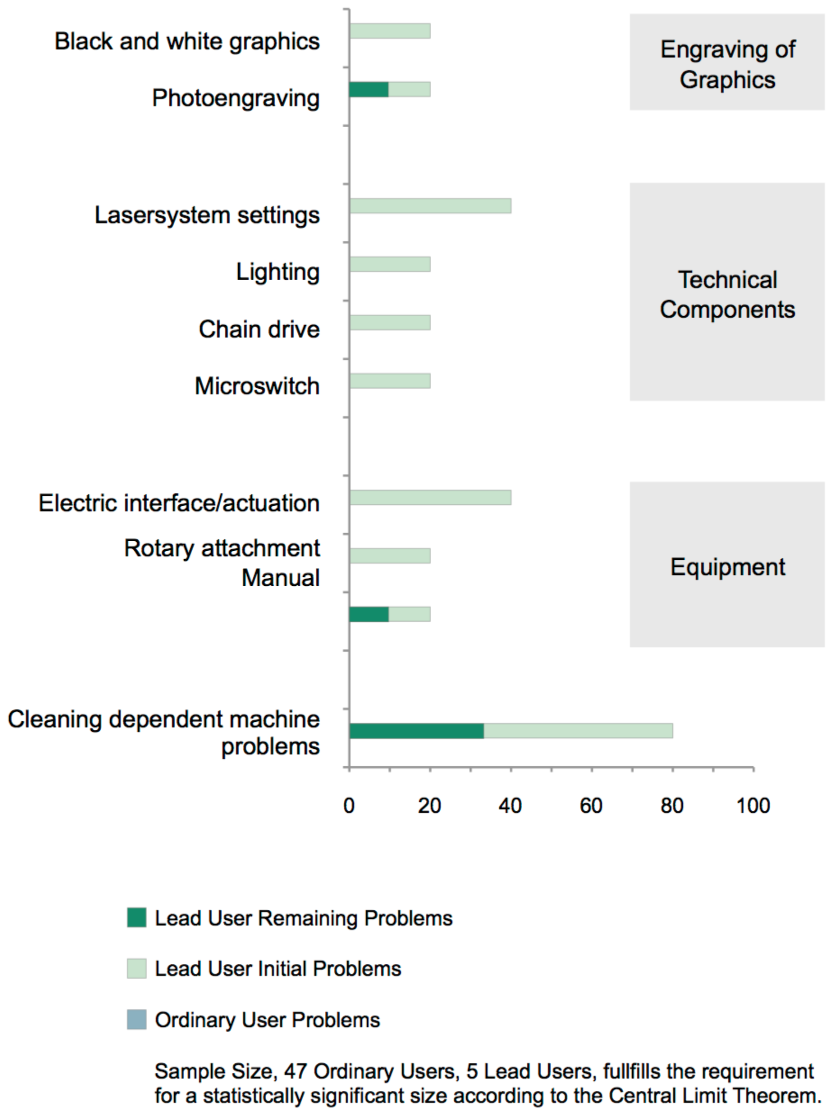

Figure IX.1. Additional Lead User Problem Areas

To get to the bottom of the differences between my lead user and non-lead user sample, I correlated (1) the lead users' initial assessments with the non-lead users ones and (2) the lead users' final assessments (after their modifications and adjustments) with the non-lead users ones. In the following, I will only discuss the most significant differences of the compared variables—for the former first, followed by the latter.

(1) In terms of the *lead users initial ($LU_{initial}$) and non-lead users (non-LU) experience* interesting to mention is, though one may assume that LU might have longer work experience on the machines, my examined lead users actually do not have a longer period of use of the manufacturer's machines. My correlation might, at first sight seem to imply that lead users have a significantly longer period of the manufacturer's CNC laser machine use (p = 0,034*, mean_ou = 4.44 years, mean_lu = 7.30 years). However, the questionnaires were conducted 3 years before the lead user interviews, which means that, when the results are adjusted, the time usage of the machines of lead and ordinary users were, with around 4 years on average, about the same. In

contrast, lead users tended to use computers longer than non-lead users before they started working with CNC laser machines ($p = 0.079^{L}$, see Figure IX.1 for more details).

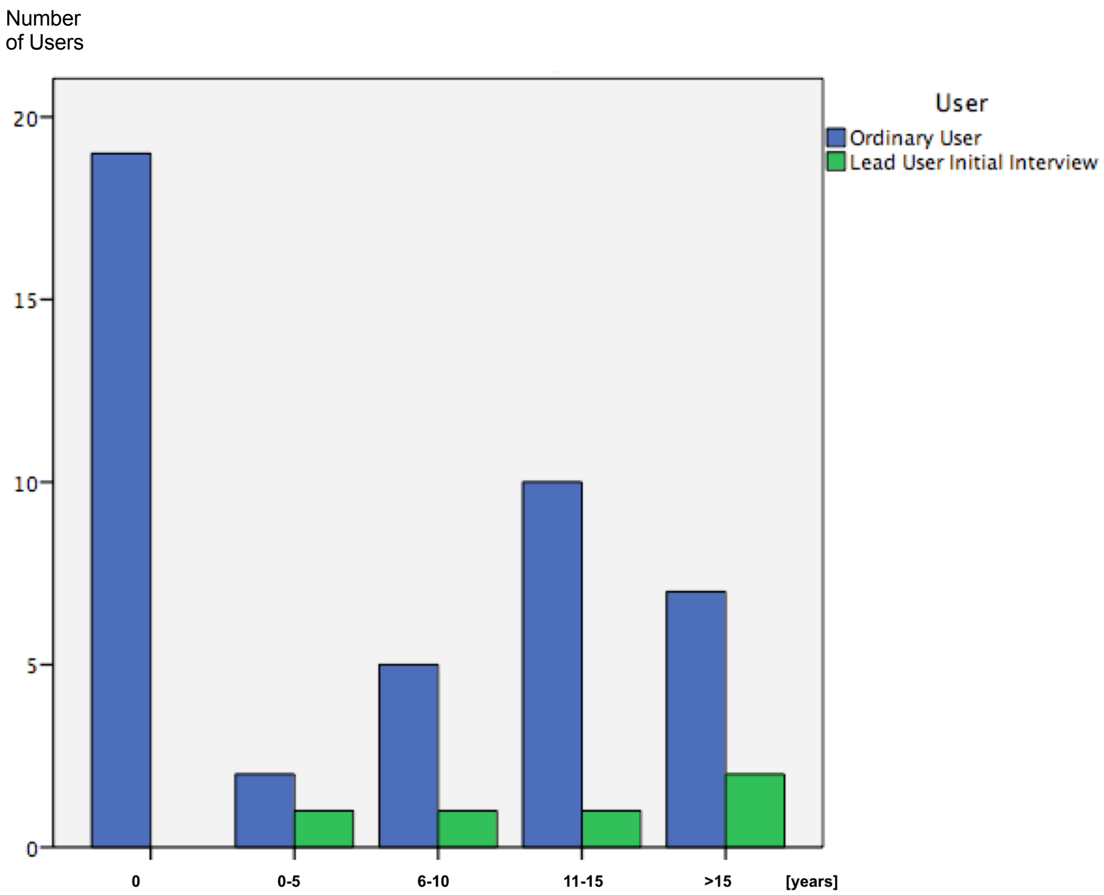

Figure IX.1. Years of Computers Usage Before Laser Systems

My data for the user comparison on how they *learned to operate the machines*, revealed two significant results.

First, more lead users than ordinary users were trained to operate the machine by the manufacturer's initial training ($p = 0.031^*$, $rho = 0.314$), which confirms prior results that my investigated lead users have some sort of autonomy in their jobs, like being work superiors and able to purchase machines etc.

Second, and more importantly, more lead users learned to operate the machines through learning by doing—as they would, in their own words refer to experimentation—with the machines ($p = 0.003^{**}$, $rho = 0.503$). More precisely 80.00% of the lead users stated in the questionnaire that they learned to operate the machine themselves, whereas only 12.77% of the non-lead users would do so. However, this result is even more significant ($p = 0.000^{***}$, $rho = 0.630$), considering the fact, that the one lead user may forgot to state in the questionnaire to have learned the machine operation by doing, though he explicitly stated it multiple times in the interview. However, for the sake of transparency, the questionnaire data was not adjusted.

Furthermore, important to mention is that more lead than non-lead users encounter problems in the *material positionability* ($p = 0.001^{***}$, $rho = 0.625$, see Table IX.1-IX.4 for more statistical details). One reason for this can be found in the lead users' higher demand on accuracy and, therefore, higher effort in positioning the material—especially for serial production and problems with the optional rotary attachments.

Table IX.1. Crosstab Material Positionability * User

		Non-Lead User	Lead User Initial Interview	Total
No Problem	Count	34	1	35
	Expected Count	30.8	4.2	35
	% within Material Positionability	0.971	0.029	1
	% within User	0.919	0.2	0.833
	% of Total	0.81	0.024	0.833
	Residual	3.2	-3.2	
	Std. Residual	0.6	-1.6	
	Adjusted Residual	4	-4	
Problem	Count	3	4	7
	Expected Count	6.2	0.8	7
	% within Material Positionability	0.429	0.571	1
	% within User	0.081	0.8	0.167
	% of Total	0.071	0.095	0.167
	Residual	-3.2	3.2	
	Std. Residual	-1.3	3.5	
	Adjusted Residual	-4	4	
Total	Count	37	5	42
	Expected Count	37	5	42
	% within Material Positionability	0.881	0.119	1
	% within User	1	1	1
	% of Total	0.881	0.119	1

Table IX.2. Chi-Square Tests Material Positionability * User

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)	Point Probability
Pearson Chi-Square	16.391[a]	1	0	0.001	0.001	
Continuity Correction[b]	11.624	1	0.001			
Likelihood Ratio	12.019	1	0.001	0.001	0.001	
Fisher's Exact Test				0.001	0.001	
Linear-by-Linear Association	16.001[c]	1	0	0.001	0.001	0.001
N of Valid Cases	42					

Table IX.3. Directional Measures Material Positionability * User

		Value	Asymp. Std. Error[a]	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.	Exact Sig.
Lambda	Symmetric	0.333	0.314	0.314	0.903	0.366	
	Material Positionability Dependent	0.429	0.241	0.241	1.371	0.17	
	User Dependent	0.2	0.473	0.473	0.379	0.705	
Goodman and Kruskal tau	Material Positionability Dependent	0.39	0.197	0.197		.000[c]	0.001
	User Dependent	0.39	0.21	0.21		.000[c]	0.001
Uncertainty Coefficient	Symmetric	0.351	0.184	0.184	1.673	.001[d]	0.001
	Material Positionability Dependent	0.318	0.177	0.177	1.673	.001[d]	0.001
	User Dependent	0.392	0.197	0.197	1.673	.001[d]	0.001

Table IX.4. Symmetric Measures Material Positionability * User

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.	Exact Sig.
Nominal by Nominal	Phi	0.625			0	0.001
	Cramer's V	0.625			0	0.001
	Contingency Coefficient	0.53			0	0.001
Interval by Interval	Pearson's R	0.625	0.169	5.06	.000[c]	0.001
Ordinal by Ordinal	Spearman Correlation	0.625	0.169	5.06	.000[c]	0.001
N of Valid Cases		42				

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

c. Based on normal approximation.

These results are reflected in the *material positioning accuracy* (p = 0.025*, rho = 0.376), as more problems were, in comparison, reported among the group of lead users. Protruding for this variable were especially zero positioning problems of the machine, which affect the quality of the work pieces' outcome.For more details on the differences between non- and lead users for this variable see Figure IX.2-3 and Table IX.5.-IX.8.

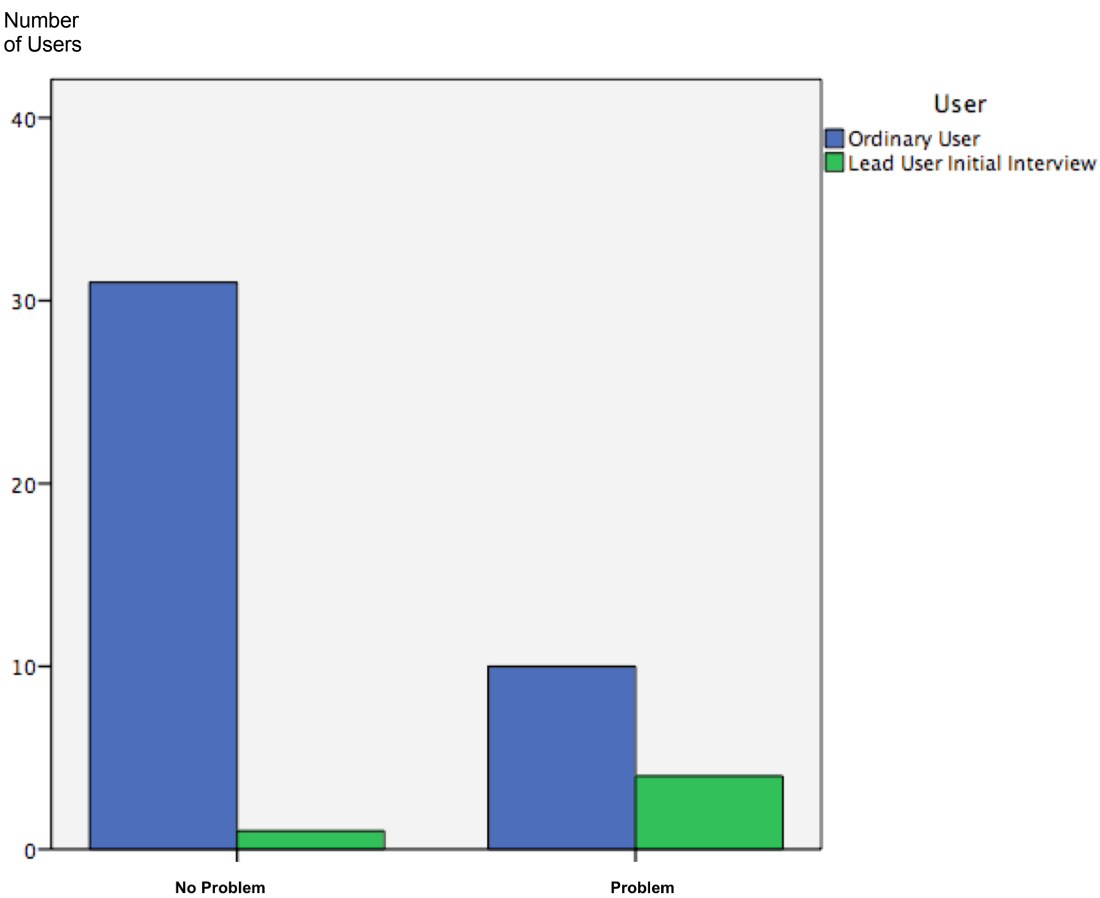

Figure IX.2. Material Positioning Accuracy

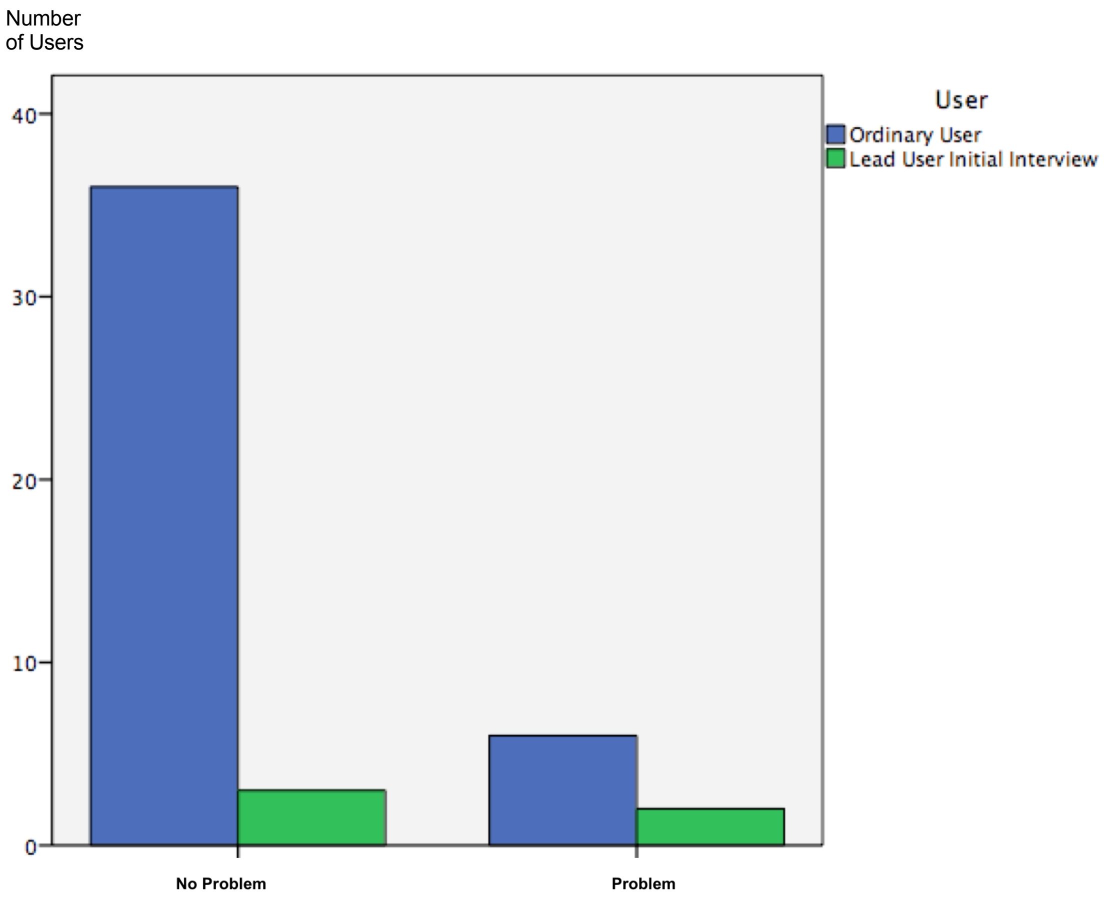

Figure IX.3. Cutting- and Engraving-Quality

Table IX.5. Crosstab Material Positioning Accuracy * User

		Non-Lead User	Lead User Initial Interview	Total
No Problem	Count	31	1	32
	Expected Count	28.5	3.5	32
	% within Material Positioning Accuracy	0.969	0.031	1
	% within User	0.756	0.2	0.696
	% of Total	0.674	0.022	0.696
	Residual	2.5	-2.5	
	Std. Residual	0.5	-1.3	
	Adjusted Residual	2.6	-2.6	
Problem	Count	10	4	14
	Expected Count	12.5	1.5	14
	% within Material Positioning Accuracy	0.714	0.286	1
	% within User	0.244	0.8	0.304
	% of Total	0.217	0.087	0.304
	Residual	-2.5	2.5	
	Std. Residual	-0.7	2	
	Adjusted Residual	-2.6	2.6	
Total	Count	41	5	46
	Expected Count	41	5	46
	% within Material Positioning Accuracy	0.891	0.109	1
	% within User	1	1	1
	% of Total	0.891	0.109	1

Table IX.6. Chi-Square Tests Material Positioning Accuracy * User

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)	Point Probability
Pearson Chi-Square	6.509[a]	1	0.011	0.025	0.025	
Continuity Correction[b]	4.148	1	0.042			
Likelihood Ratio	5.976	1	0.014	0.025	0.025	
Fisher's Exact Test				0.025	0.025	
Linear-by-Linear Association	6.368[c]	1	0.012	0.025	0.025	0.023
N of Valid Cases	46					

a. 2 cells (50.0%) have expected count less than 5. The minimum expected count is 1.52.

b. Computed only for a 2x2 table

c. The standardized statistic is 2.523.

Table IX.7. Directional Measures Material Positioning Accuracy * User

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.	Exact Sig.
Lambda	Symmetric	0.158	0.098	1.369	0.171	
	Material Positioning Accuracy Dependent	0.214	0.142	1.369	0.171	
	User Dependent	0	0	.[c]	.[c]	
Goodman and Kruskal tau	Material Positioning Accuracy Dependent	0.142	0.099		.012[d]	0.025
	User Dependent	0.142	0.109		.012[d]	0.025
Uncertainty Coefficient	Symmetric	0.136	0.104	1.241	.014[e]	0.025
	Material Positioning Accuracy Dependent	0.106	0.085	1.241	.014[e]	0.025
	User Dependent	0.189	0.137	1.241	.014[e]	0.025

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

c. Cannot be computed because the asymptotic standard error equals zero.

d. Based on chi-square approximation

e. Likelihood ratio chi-square probability.

Table IX.8. Symmetric Measures Material Positioning Accuracy * User

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.	Exact Sig.
Nominal by Nominal	Phi	0.376			0.011	0.025
	Cramer's V	0.376			0.011	0.025
	Contingency Coefficient	0.352			0.011	0.025
Interval by Interval	Pearson's R	0.376	0.145	2.693	.010[c]	0.025
Ordinal by Ordinal	Spearman Correlation	0.376	0.145	2.693	.010[c]	0.025
N of Valid Cases		46				

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

c. Based on normal approximation.

More negative reports in the *reachability of work pieces* of the lead users in comparison to the non-lead user ones ($p = 0.096^{L}$, $rho = 0.286$), are a consequence of cutting small pieces, which can drop underneath the working table and, hence, cannot be reached properly by the users. As this might be a machine specific issue, I excluded all machine types other than the one used by all of the lead users[7] from the dataset. Recalculation of the independency of the variables resulted in a slightly higher correlation ($p = 0.057^{L}$, rho = 0.510), which corroborates the coherence even more. In the following, Figure IX.4 will make the differences between non-and lead users more vivid, whereas Table IX.9-IX.12 will reveal more statistical details.

[7] One lead user worked on an older version of the same machine type and was therefore excluded from this data set.

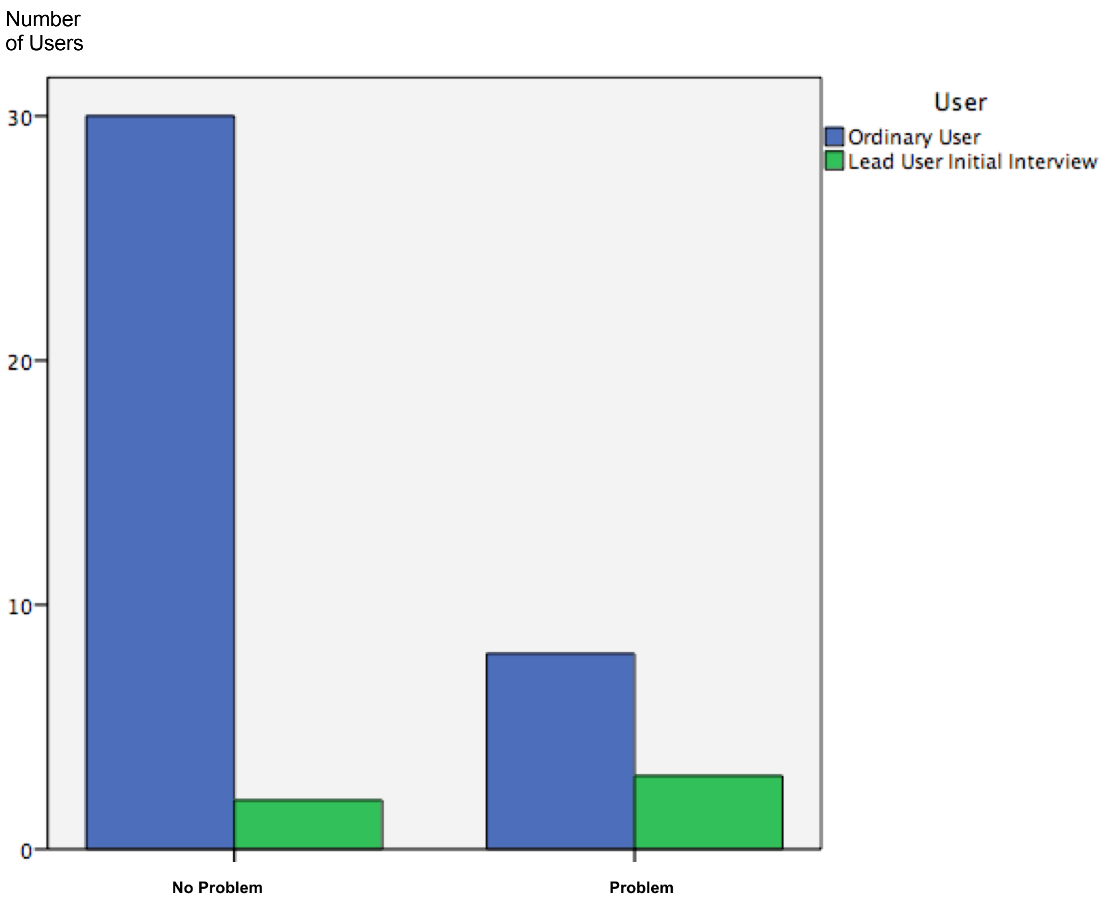

Figure IX.4. Reachability of Workpieces

Table IX.9. Crosstab Workpiece Reachability * User

		Non-Lead User	Lead User Initial Interview	Total
No Problem	Count	30	2	32
	Expected Count	28.3	3.7	32
	% within Workpiece Reachability	0.938	0.063	1
	% within User	0.789	0.4	0.744
	% of Total	0.698	0.047	0.744
	Residual	1.7	-1.7	
	Std. Residual	0.3	-0.9	
	Adjusted Residual	1.9	-1.9	
Problem	Count	8	3	11
	Expected Count	9.7	1.3	11
	% within Workpiece Reachability	0.727	0.273	1
	% within User	0.211	0.6	0.256
	% of Total	0.186	0.07	0.256
	Residual	-1.7	1.7	
	Std. Residual	-0.6	1.5	
	Adjusted Residual	-1.9	1.9	
Total	Count	38	5	43
	Expected Count	38	5	43
	% within Workpiece Reachability	0.884	0.116	1
	% within User	1	1	1
	% of Total	0.884	0.116	1

Table IX.10. Chi-Square Tests Workpiece Reachability * User

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)	Point Probability
Pearson Chi-Square	3.521[a]	1	0.061	0.096	0.096	
Continuity Correction[b]	1.772	1	0.183			
Likelihood Ratio	3.059	1	0.08	0.306	0.096	
Fisher's Exact Test				0.096	0.096	
Linear-by-Linear Association	3.439[c]	1	0.064	0.096	0.096	0.085
N of Valid Cases	43					

Table IX.11. Directional Measures Workpiece Reachability * User

		Approx. T[b]	Approx. Sig.	Exact Sig.
Lambda	Symmetric	0.448	0.654	
	Workpiece Reachability Dependent	0.448	0.654	
	User Dependent	.[c]	.[c]	
Goodman and Kruskal tau	Workpiece Reachability Dependent		.064[d]	0.096
	User Dependent		.064[d]	0.096
Uncertainty Coefficient	Symmetric	0.841	.080[e]	0.306
	Workpiece Reachability Dependent	0.841	.080[e]	0.306
	User Dependent	0.841	.080[e]	0.306

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

c. Cannot be computed because the asymptotic standard error equals zero.

d. Based on chi-square approximation

e. Likelihood ratio chi-square probability.

Table IX.12. Symmetric Measures Workpiece Reachability * User

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.	Exact Sig.
Nominal by Nominal	Phi	0.286			0.061	0.096
	Cramer's V	0.286			0.061	0.096
	Contingency Coefficient	0.275			0.061	0.096
Interval by Interval	Pearson's R	0.286	0.173	1.912	.063[c]	0.096
Ordinal by Ordinal	Spearman Correlation	0.286	0.173	1.912	.063[c]	0.096
N of Valid Cases		43				

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

c. Based on normal approximation.

Interestingly, none of the lead users applied *vacuum tables* for machining, as they found their own, better suitable solutions to process the products, which are normally processed with this kind of tables.

That lead users encounter more problems in *cleaning the machine working space* than non-lead users ($p = 0.012^*$, $rho = 0.435$) and that their assessment differs in the same way for the exhaust system maintenance ($p = 0.044^*$, $rho = 0.398$), can be attributed to the lead users' higher precision/accuracy aspirations. Please see Figure IX.5 and Table IX.13-15 for more statistical details on non- and lead user evaluation differences for cleaning the machine's working space, and Table IX.16-IX.19 for the maintenance of the machine's exhaust system.

To keep the machine clean is a prerequisite for accurate processing, as even the smallest dust particle can influence the working process and, consequently, the outcome. An example would be that dust-particles on the lens of the photoelectric barrier could lead to a deviation in the laser beam focusing, and, consequently, result in a greater laser insertion into the material, leading to non-sharp results. Therefore, in all of the nonstructured parts of my lead user interviews, one of the prominent topics expressed was the great demand for meticulously accurate and detailed cleaning of the machines.

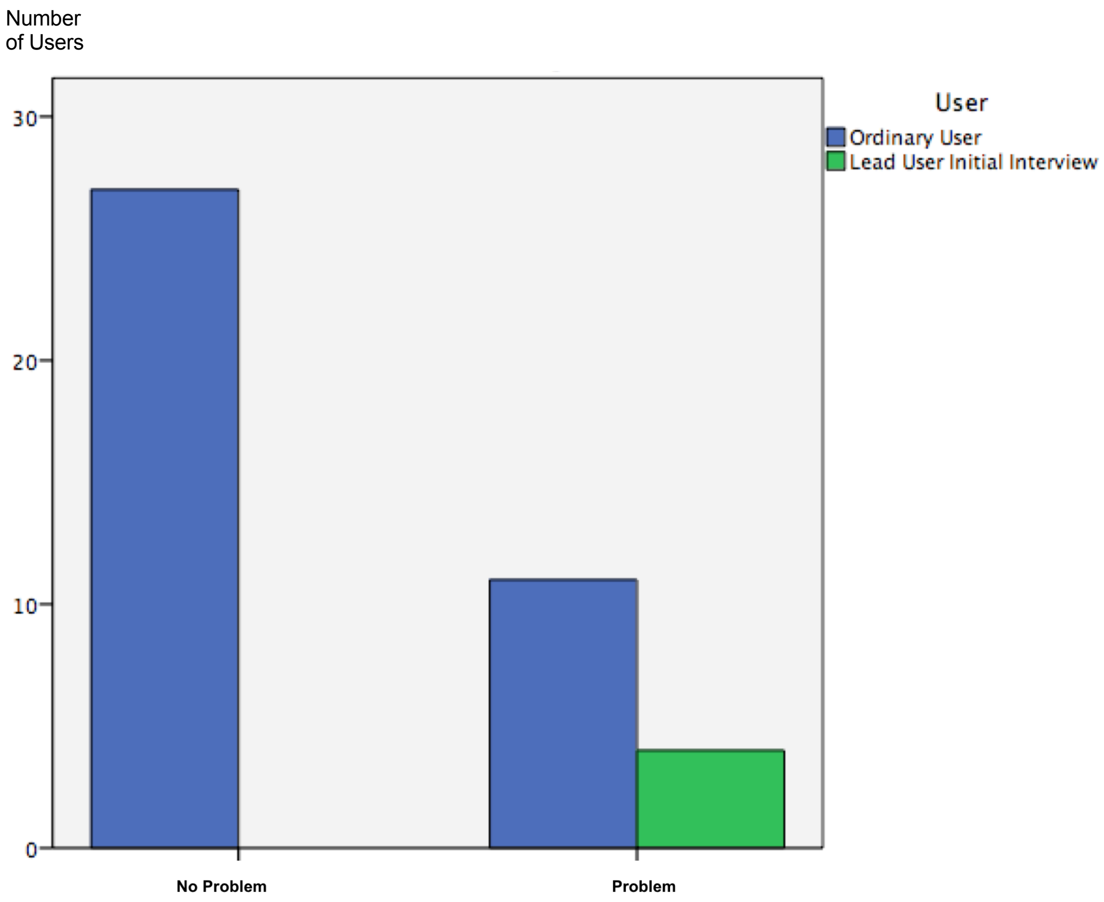

Figure IX.5. Cleaning of the Machine's Working Area

Table IX.13. Crosstab Cleaning of the Machine's Working Area * User Crosstab

		Non-Lead User	Lead User Initial Interview	Total
No	Count	27	0	27
	Expected Count	24.4	2.6	27
	% within Cleaning of the Machine's Working Area	1	0	1
	% within User	0.711	0	0.643
	% of Total	0.643	0	0.643
	Residual	2.6	-2.6	
	Std. Residual	0.5	-1.6	
	Adjusted Residual	2.8	-2.8	
Yes	Count	11	4	15
	Expected Count	13.6	1.4	15
	% within Cleaning of the Machine's Working Area	0.733	0.267	1
	% within User	0.289	1	0.357
	% of Total	0.262	0.095	0.357
	Residual	-2.6	2.6	
	Std. Residual	-0.7	2.2	
	Adjusted Residual	-2.8	2.8	
Total	Count	38	4	42
	Expected Count	38	4	42
	% within Cleaning of the Machine's Working Area	0.905	0.095	1
	% within User	1	1	1
	% of Total	0.905	0.095	1

Table IX.14. Directional Measures Cleaning of the Machine's Working Area * User

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.	Exact Sig.
Lambda	Symmetric	0.211	0.071	2.103	0.035	
	Cleaning of the Machine's Working Area Dependent	0.267	0.114	2.103	0.035	
	User Dependent	0	0	.[c]	.[c]	
Goodman and Kruskal tau	Cleaning of the Machine's Working Area Dependent	0.189	0.055		.005[d]	0.012
	User Dependent	0.189	0.09		.005[d]	0.012
Uncertainty Coefficient	Symmetric	0.222	0.085	2.123	.003[e]	0.012
	Cleaning of the Machine's Working Area Dependent	0.165	0.078	2.123	.003[e]	0.012
	User Dependent	0.341	0.075	2.123	.003[e]	0.012

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

c. Cannot be computed because the asymptotic standard error equals zero.

d. Based on chi-square approximation

e. Likelihood ratio chi-square probability.

Table IX.15. Symmetric Measures Cleaning of the Machine’s Working Area * User

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.	Exact Sig.
Nominal by Nominal	Phi	0.435			0.005	0.012
	Cramer's V	0.435			0.005	0.012
	Contingency Coefficient	0.399			0.005	0.012
Interval by Interval	Pearson's R	0.435	0.105	3.058	.004[c]	
Ordinal by Ordinal	Spearman Correlation	0.435	0.105	3.058	.004[c]	
N of Valid Cases		42				

Table IX.16. Crosstab Exhaust System Maintenance * User

		Non-Lead User	Lead User Initial Interview	Total
No	Count	22	0	22
	Expected Count	20.1	1.9	22
	% within Exhaust System Maintenance	1	0	1
	% within User	0.688	0	0.629
	% of Total	0.629	0	0.629
	Residual	1.9	-1.9	
	Std. Residual	0.4	-1.4	
	Adjusted Residual	2.4	-2.4	
Yes	Count	10	3	13
	Expected Count	11.9	1.1	13
	% within Exhaust System Maintenance	0.769	0.231	1
	% within User	0.313	1	0.371
	% of Total	0.286	0.086	0.371
	Residual	-1.9	1.9	
	Std. Residual	-0.5	1.8	
	Adjusted Residual	-2.4	2.4	
Total	Count	32	3	35
	Expected Count	32	3	35
	% within Exhaust System Maintenance	0.914	0.086	1
	% within User	1	1	1
	% of Total	0.914	0.086	1

Table IX.17. Chi-Square Tests Exhaust System Maintenance * User

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)	Point Probability
Pearson Chi-Square	5.553[a]	1	0.018	0.044	0.044	
Continuity Correction[b]	2.999	1	0.083			
Likelihood Ratio	6.43	1	0.011	0.044	0.044	
Fisher's Exact Test				0.044	0.044	
Linear-by-Linear Association	5.394[c]	1	0.02	0.044	0.044	0.044
N of Valid Cases	35					

a. 2 cells (50.0%) have expected count less than 5. The minimum expected count is 1.11.

b. Computed only for a 2x2 table

c. The standardized statistic is 2.323.

Table IX.18. Directional Measures Exhaust System Maintenance * User

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.	Exact Sig.
Lambda	Symmetric	0.188	0.077	1.811	0.07	
	Exhaust System Maintenance Dependent	0.231	0.117	1.811	0.07	
	User Dependent	0	0	.[c]	.[c]	
Goodman and Kruskal tau	Exhaust System Maintenance Dependent	0.159	0.051		.020[d]	0.044
	User Dependent	0.159	0.088		.020[d]	0.044
Uncertainty Coefficient	Symmetric	0.193	0.087	1.82	.011[e]	0.044
	Exhaust System Maintenance Dependent	0.139	0.077	1.82	.011[e]	0.044
	User Dependent	0.314	0.078	1.82	.011[e]	0.044

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

c. Cannot be computed because the asymptotic standard error equals zero.

d. Based on chi-square approximation

e. Likelihood ratio chi-square probability.

Table IX.19. Symmetric Measures Exhaust System Maintenance * User

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.	Exact Sig.
Nominal by Nominal	Phi	0.398			0.018	0.044
	Cramer's V	0.398			0.018	0.044
	Contingency Coefficient	0.37			0.018	0.044
Interval by Interval	Pearson's R	0.398	0.112	2.495	.018[c]	0.044
Ordinal by Ordinal	Spearman Correlation	0.398	0.112	2.495	.018[c]	0.044
N of Valid Cases		35				

Though criticized by the ordinary users, lead users judge the *self-descriptiveness of the software symbols* even more critically (p = 0.035*, rho = 0.364, and Table IX.20-IX23 for more statistical details). The cause for this critical assessment (despite the lead users' generally better evaluation) might be found in the inability to solve this problem and hence, the only feasible approach to adjust to it.

Table IX.20. Crosstab Self-Explanatory Symbols * User

		Non-Lead User	Lead User Initial Interview	Total
No Problem	Count	27	1	28
	Expected Count	24.7	3.3	28
	% within Self-Explanatory Symbols	0.964	0.036	1
	% within User	0.73	0.2	0.667
	% of Total	0.643	0.024	0.667
	Residual	2.3	-2.3	
	Std. Residual	0.5	-1.3	
	Adjusted Residual	2.4	-2.4	
Problem	Count	10	4	14
	Expected Count	12.3	1.7	14
	% within Self-Explanatory Symbols	0.714	0.286	1
	% within User	0.27	0.8	0.333
	% of Total	0.238	0.095	0.333
	Residual	-2.3	2.3	
	Std. Residual	-0.7	1.8	
	Adjusted Residual	-2.4	2.4	
Total	Count	37	5	42
	Expected Count	37	5	42
	% within Self-Explanatory Symbols	0.881	0.119	1
	% within User	1	1	1
	% of Total	0.881	0.119	1

Table IX.21. Chi-Square Tests Self-Explanatory Symbols * User

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)	Point Probability
Pearson Chi-Square	5.562[a]	1	0.018	0.035	0.035	
Continuity Correction[b]	3.434	1	0.064			
Likelihood Ratio	5.282	1	0.022	0.035	0.035	
Fisher's Exact Test				0.035	0.035	
Linear-by-Linear Association	5.430[c]	1	0.02	0.035	0.035	0.033
N of Valid Cases	42					

Table IX.22. Directional Measures Self-Explanatory Symbols * User

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.	Exact Sig.
Lambda	Symmetric	0.158	0.098	1.371	0.17	
	Self-Explanatory Symbols Dependent	0.214	0.142	1.371	0.17	
	User Dependent	0	0	.[c]	.[c]	
Goodman and Kruskal tau	Self-Explanatory Symbols Dependent	0.132	0.098		.020[d]	0.035
	User Dependent	0.132	0.107		.020[d]	0.035
Uncertainty Coefficient	Symmetric	0.126	0.102	1.18	.022[e]	0.035
	Self-Explanatory Symbols Dependent	0.099	0.083	1.18	.022[e]	0.035
	User Dependent	0.172	0.133	1.18	.022[e]	0.035

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

c. Cannot be computed because the asymptotic standard error equals zero.

d. Based on chi-square approximation

e. Likelihood ratio chi-square probability.

Table IX.23. Symmetric Measures Self-Explanatory Symbols * User

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.	Exact Sig.
Nominal by Nominal	Phi	0.364			0.018	0.035
	Cramer's V	0.364			0.018	0.035
	Contingency Coefficient	0.342			0.018	0.035
Interval by Interval	Pearson's R	0.364	0.147	2.471	.018[c]	0.035
Ordinal by Ordinal	Spearman Correlation	0.364	0.147	2.471	.018[c]	0.035
N of Valid Cases		42				

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

c. Based on normal approximation.

(2) In terms of the *lead users final (LU_{final}) and non-lead users (non-LU)* correlations and considering the LU_{final} correlation results above, it is important to mention the following aspects:

After the lead users' innovations with stencils, other devices to position the material in the machine, and similar solutions, no significant differences in the evaluation of the *material positionability* ($p = 0.702$, $rho = -0.092$) and the *material positioning accuracy* ($p = 0.272$, $rho = -0.177$) can be found between the non-lead users and the lead users.

Similar results can be found for the *reachability of work pieces*, where no significant differences in the assessment can be stated between lead and non-lead users ($p = 0.673$, $rho = 0.001$), though their ability to work more precisely on the machines lead them to cut even the smallest pieces.

That lead users encounter still more problems in *cleaning the machine working space* than non-lead users ($p = 0.095^{L}$, $rho = 0.279$) can be attributed to the fact that no fully satisfying innovations could be found due to machine design constraints. In order to do so, it would have required the lead users to redesign the machine's inner mantle.

As for the *self-descriptiveness of the software symbols*, after experimenting with the symbols and understanding the functions—though the result is not significant—the group of lead users evaluated the symbols slightly better than the non-lead users ($p = 0.237$, $rho = 0.196$).

Interestingly, though not significant initially, the lead users' final evaluation of the *dust exposure and odor pollution* was significantly better than that of the non-lead users ($p = 0.010^{**}$, $rho = -0.381$). These highly significant differences can be attributed to the lead users technical understanding and acceptance of the odor emission, which they consider as natural when working with certain materials (e.g. foam).

The bias discussion of this chapter will revolve about the power of my analysis. One might criticize three influential factors, which I considered carefully—(1) distinguishing between non-and lead users, (2) mixing qualitative and quantitative data and, (3) dichotomizing the variables for better comparability. Where my *Discussion Within the Greater Context* is leading to is already implied by the brief depiction of my findings. However, in this section I will briefly summarize and generalize my specific findings

CHAPTER X

Thesis Conclusion: Theoretical Contributions from Field to Academia

This chapter should summarize my research explorations and show its contribution to the landscape of innovation theory. To do so, I will generalize the findings of my field studies (Part 2) and understand them by consulting chapters I and II (Part 1) of my doctoral thesis. I will discuss the contributions from a user's and manufacturer's perspective and will focus on the causes I found for why, when and how users innovate and how manufacturers deal with it.

From a user's perspective, my research findings suggest, that the users own capabilities are key to solve their occurring problems. However, these abilities stem from different factors, like (1) their past experiences which include, but are not limited to, the socialization process and education, working background etc. as well as (2) their own abilities to draw on and connect their inputs and (3) how their environment/working condition supports them in the problem-solving process.

(1) My data depicts that the time exposure to a product is not affected by whether or not someone is a lead user (see Figure X.1. for differences between non- and lead users in years of usage of laser systems and Figure X.2. for the manufacturer's machines). Nevertheless, experience is an influencing factor (see Figure X.3. for differences between non- and lead users' highest educational attainment, and Figure X.4 for a comparison of the non- and lead users' technical training /engineering

apprenticeship). The users socialization process influences their interaction with the machines. More freedom in the user's (past) personal development may lead to an open approach to the systems, and hence to more experimentation with the device. This experimentation is crucial to learning how to operate the machine, their functions, and to increase the productivity, as for example no manual or training would teach the most suitable, individual work flow. This personal freedom at work is also reflected in my data, since all of my lead users hold a superior position in the workplace.

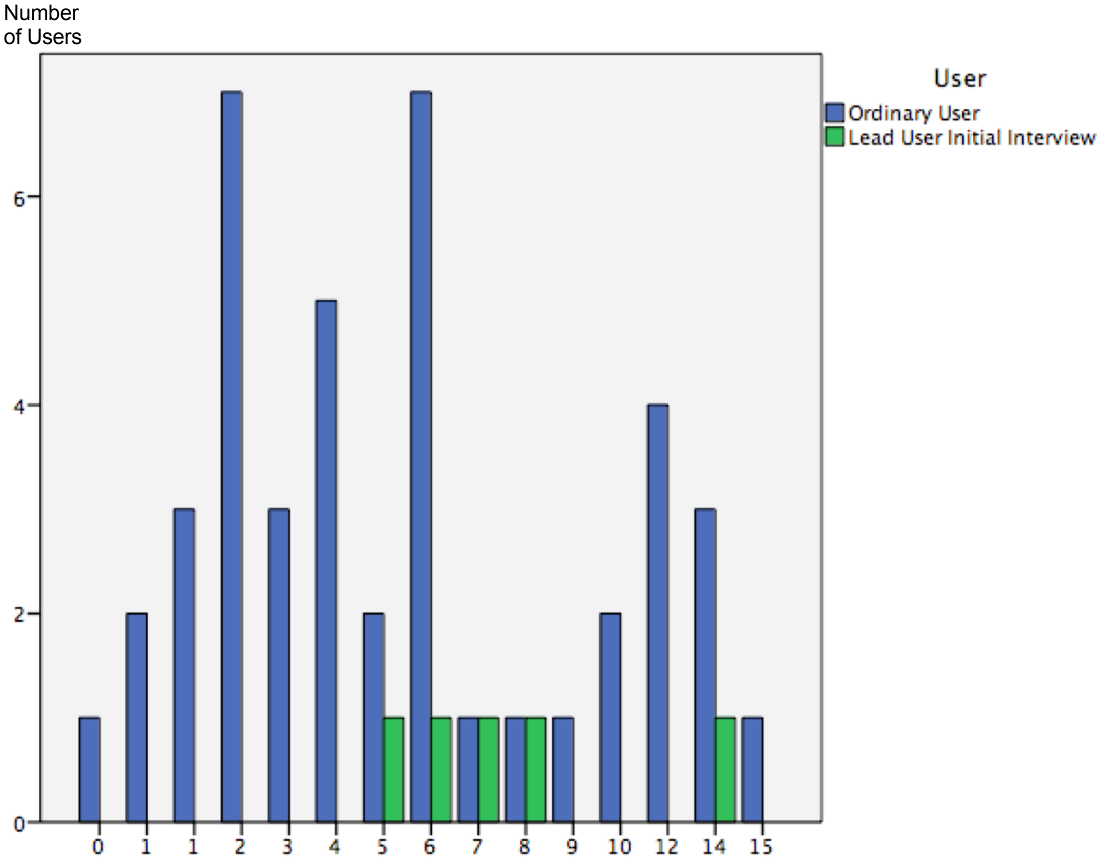

Figure X.1. Years of Usage of Laser Systems

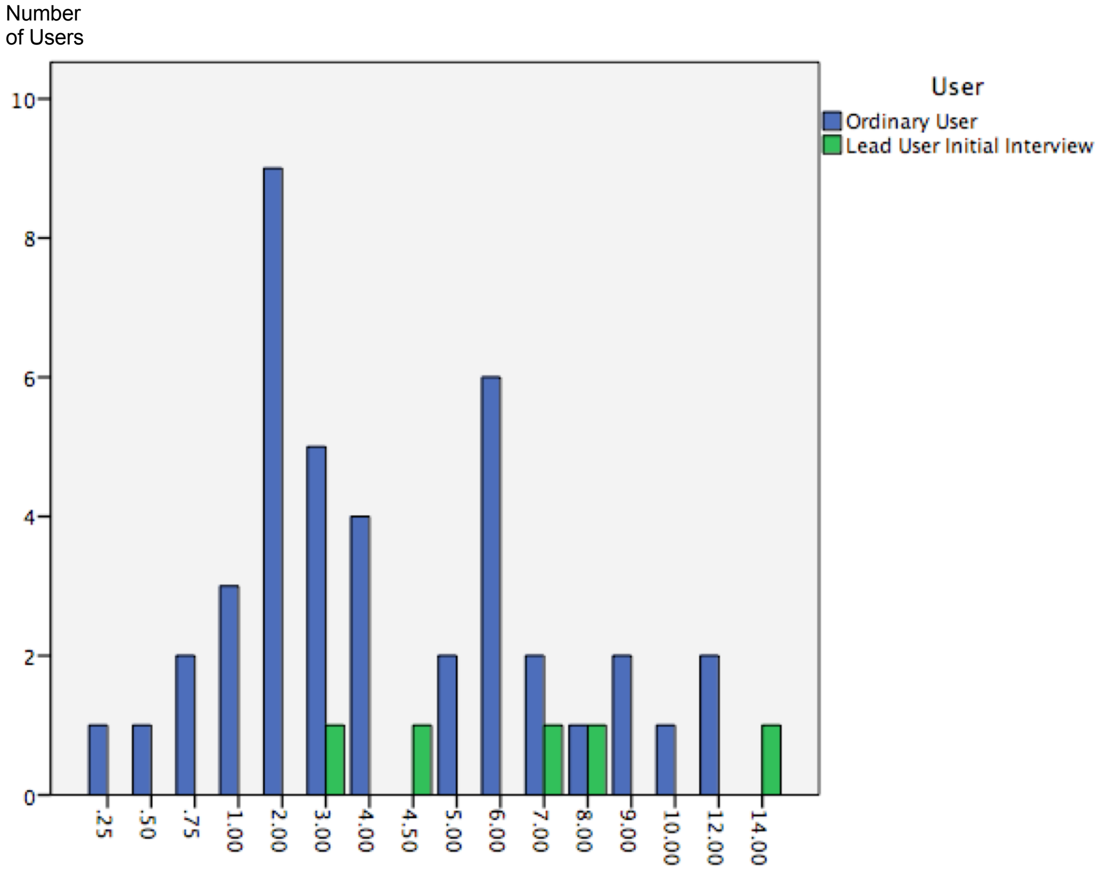

Figure X.2. Years of Usage of the Manufacturer's Laser Systems

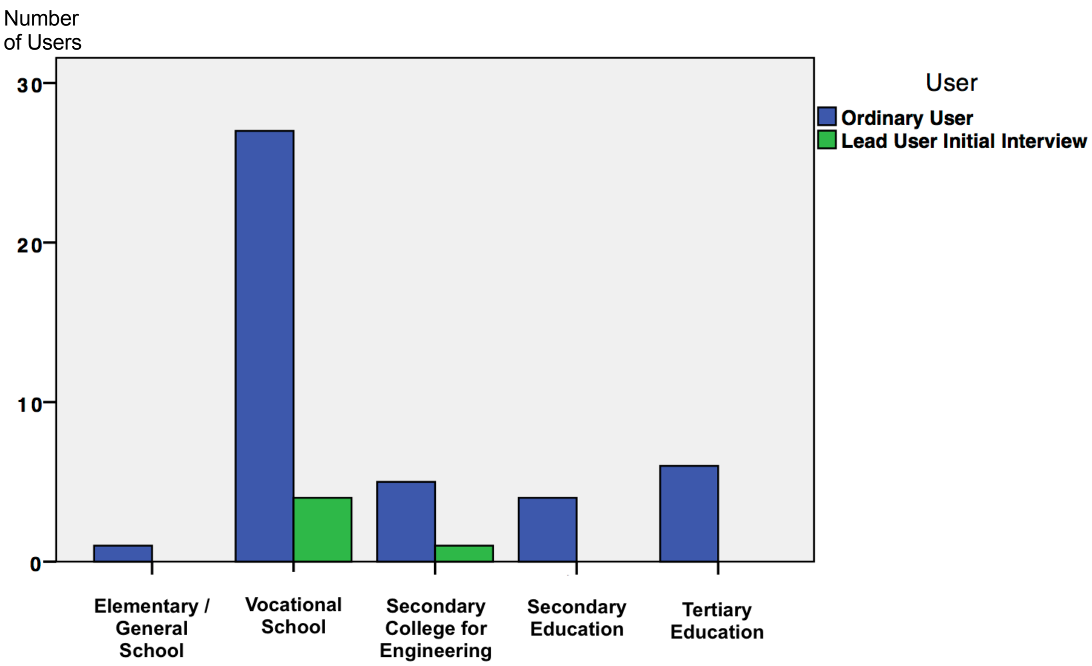

Figure X.3. Highest Completed Educational Attainment

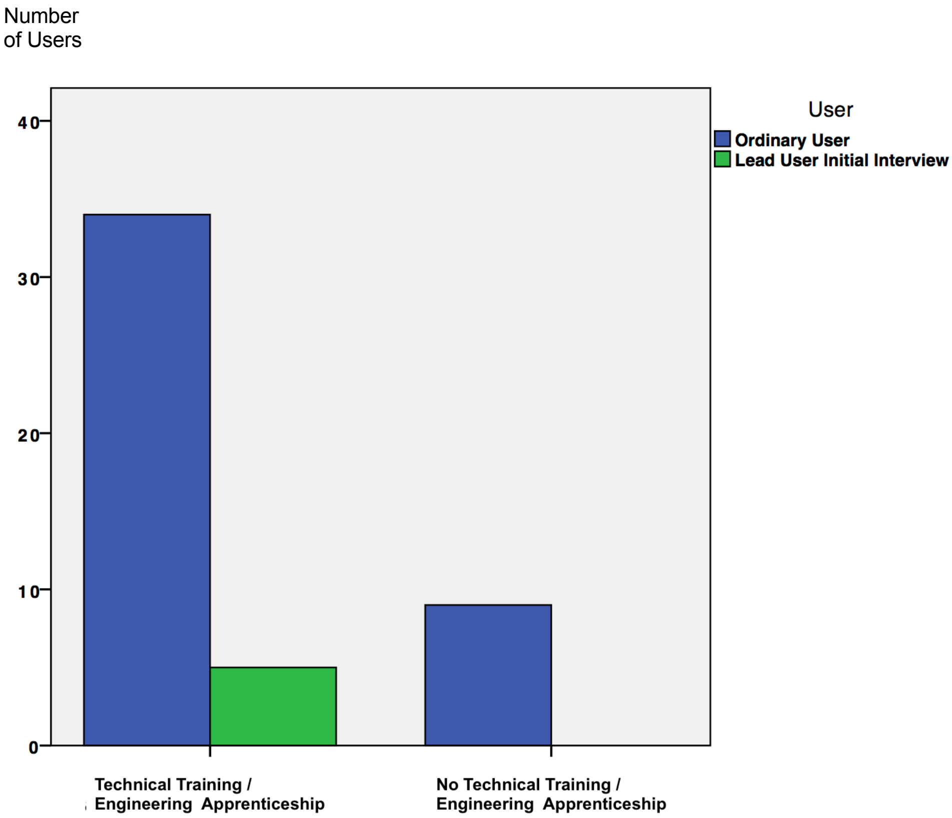

Figure X.4. Technical Training / Engineering Apprenticeship Background

(2) My findings further confirm what has been discussed in other places (von Hippel, 1977; von Hippel, 2005) that lead users draw analogies from other fields to solve their own problems—my investigated lead user sample not only searched online for inspiration, but they also sought remedies from the manufacturer, other user firms which they assumed to

have already dealt with the same issue as well as experts, for what they think the source of problem is. However, what was stated in passing (Hippel, 2005, p. 94) is confirmed by my data, viz. that the user's personal background leads to different innovations due to different solution spaces.

(3) Exogenous factors can further influence the users' innovative activity, as it is a question of how the consequently necessary experimentation, as well as implementation of their ideas, not only with artifacts (like tools, materials, does the equipment allow to innovate), but also with the social working conditions (e.g. if innovative solutions get incentivized rather than being strictly time oriented to carry out the customer's orders / short-term vs. long term oriented, may material/equipment be ordered in order to try alternate approaches) is supported. Therefore, the decision-making ability, which is necessary for the users to innovate, might be the main determining factor for why all of the lead users had their own scope of responsibility where no higher hierarchy within the organization intervened in terms of resource allocation.

Once more attributed to the factors of freedom at work and experimentation, are my findings that lead users may also continuously innovate to extend their scope of applications beyond the basic (specific) application(s) for which they initially acquired the machines. Thus, I will disclose this (extension of applications) and other factors, which affect the learning curve and address what has not been discussed in literature so far—an initial slope of the learning curve before its actual drop.

Though my research data is coherent with conventional wisdom and with most of the prescriptive literature, von Hippel's (2005) hypothesis that users' freely reveal their information is at odds with my findings. The lead users at the top end of my sample, only partially revealed their information, since they were so specialized and/or advanced in their applications, that they would lose their competitive advantage by sharing their solution approach.

From a *manufacture's perspective*, several challenges, considering my pieces of information, have to be faced.

My sample lead users were in communicational exchange with the manufacturer's field force and contacted them in case of occurring problems with the machines or for servicing or maintenance reasons. I am even aware of one lead user who would travel to the manufacturer, when problems occurred which he would not be able to solve on his own after several iteration processes in his own experimentation efforts. The products he was struggling with, he would bring to the manufacturer's headquarters and tested them with the company's engineers until they would come up with a sufficient solution together. Due to this exchange, the manufacturer also benefited, as they would find out about new applications and would find alternate ways to use and process with the machines. In turn, the manufacturer would diffuse the gained knowledge to other users via their online platform, communication of field staff or at trade fairs. Therefore, a symbiosis between manufacturer and user firms/individual users is mandatory for natural growth of organizations—as lead users come up with commercially successful innovations, extend the machine's area of application and show alternate ways of processing and operating.

Therefore, I hypothesize, that the pace of technological change can be postponed by subsequently involving lead users knowledge into the organizations development process. As lead users strive to innovate or change their way of operation and adjust to inefficient processes, which they cannot solve on their own in order to make their efforts more economically valuable (faster processes, outcomes of higher quality, better use of machines, etc) the manufacturer will consequently benefit from their knowledge. Hence, as manufacturers generally strive for better products along a sustaining development curve (cf. Christensen and Bower, 1996; Christensen and Rosenbloom, 1995), they would enforce a natural growth of the products and extend the cycle of continuous designs (cf. Anderson and Tushman, 1990). Therefore, these lead user inputs would show competence enhancing innovations, and bringing the operating cost of their products down, without a necessary overall discontinuous design or competence destroying innovation.

In this way, actual designs would be used to a better—and more efficient—extent, being not only of micro- but also of macro economic influence. With competence enhancing innovations (cf. Abernathy, 1976;

Henderson, 1995; Henderson and Clark, 1990; Kaplan and Tripsas, 2008), the manufacturers' effort to come up with new model versions are significantly lower than designing an entirely new product, which would entail R&D and plant set-up costs (for new tools etc.). The manufacturers would continue to further exploit their machines, and production site, thus continue to progress on the learning curve within the production facilities, whilst operating at peak efficiency and economies of scale, as more of the same parts could be acquired at cheaper costs. The positive macroeconomics effect, from a social welfare perspective, would be a consequence of avoiding the scattered locations in the search for alternate or discontinuous designs as well as an avoidance of a waste of resources in unnecessary competence-destroying technology, and subsequent market uncertainty, at an earlier point in time as indispensable or best applicable. Therefore, the competitive point of market entry for alternate products would be shifted to lower costs for processing and would subsequently avoid coming up with competence destroying designs where existing products could achieve same performance levels. Hence, the times of uncertain designs would also be postponed to points where actual designs, and their subsequent processes in operations, cannot be further exploited and the cost curve reached its absolute minimum.

Consequently, embedding lead users knowledge into research and development is not optional—it is essential for efficient and effective using of (limited) micro economical and macro economical resources.

(Page intentionally left blank)

Bibliography

Abernathy, W.J., 1976. The productivity dilemma: roadblock to innovation in the automobile industry. Harvard University, Graduate School of Business, Boston.

Abernathy, W.J., 1969. Parallel strategies in development projects. Manag. Sci. J. Inst. Oper. Res. Manag. Sci. 15, 486.

Abernathy, W.J., Rosenbloom, R.S., 1968. Parallel and sequential R&D strategies: Application of a simple model. Eng. Manag. IEEE Trans. On EM-15, 2–10. doi:10.1109/TEM.1968.6446996

Abernathy, W.J., Wayne, K., 1974. Limits of the learning curve. Harv. Bus. Rev. 52, 109.

Adler, P.S., Clark, K.B., 1991. Behind the learning curve: A sketch of the learning process. Manag. Sci. 37, 267–281.

A. Garg, P.M., 1961. The aircraft progress curve modified for design changes. J. Ind. Eng. 12, 23–27.

Alchian, A., 1963. Reliability of Progress Curves in Airframe Production. Econometrica 31, 679. doi:10.2307/1909166

Alchian, A., 1959. , in: The Allocation of Economic Resources; Essays in Honor of Bernard Francis Haley, Stanford Studies in History, Economics, and Political Science, v. 17. Stanford, Calif, Stanford University Press.

Alexander, C., 1964. Notes on the synthesis of form. Harvard University Press, Cambridge.

Allen, T.J., 1966a. Managing the flow of scientific and technological information (Ph.D.). Massachusetts Institute of Technology.

Allen, T.J., 1966b. Studies of the problem-solving process in engineering design. Eng. Manag. IEEE Trans. On EM-13, 72–83. doi:10.1109/TEM.1966.6447087

Anderson, P., Tushman, M.L., 1990. Technological Discontinuities and Dominant Designs: A Cyclical Model of Technological Change. Adm. Sci. Q. 35, 604. doi:10.2307/2393511

Andress, F.J., 1954. The Learning Curve As a Production Tool. Harv. Bus. Rev. 32, 87–97.

Argyris, C., 1977. Double loop learning in organizations. Harv. Bus. Rev. 55, 115–125.

Arrow, K.J., 1984. The economics of information., Arrow, Kenneth Joseph, 1921- Essays; v. 4. Y. Belknap Press of Harvard University Press, Cambridge, Mass.

Arrow, K.J., 1962. The Economic Implications of Learning by Doing. Rev. Econ. Stud. 29, 155. doi:10.2307/2295952

Asher, H., 1956a. Cost-quantity relationships in the airframe industry. Rand Corp, Santa Monica, Calif.

Asher, H., 1956b. Cost-quantity relationships in the airframe industry. Rand Corp, Santa Monica, Calif.

Baldwin, C., Hienerth, C., von Hippel, E., 2006. How user innovations become commercial products: A theoretical investigation and case study. Res. Policy 35, 1291–1313.

Baldwin, C., von Hippel, E., 2011. Modeling a Paradigm Shift: From Producer Innovation to User and Open Collaborative Innovation. Organ. Sci. 22, 1399–1417. doi:10.1287/orsc.1100.0618

Baloff, N., 1971. Extension of the Learning Curve -- Some Empirical Results. Oper. Res. Q. 1970-1977 22, 329–340. doi:10.2307/3008186

Baloff, N., 1970. Startup Management. IEEE Trans. Eng. Manag. 17, 132–141.

Baloff, N., 1966a. The Learning Curve--Some Controversial Issues. J. Ind. Econ. 14, 275–282. doi:10.2307/2097555

Baloff, N., 1966b. Startups in Machine-Intensive Production Systems. J. Ind. Eng. 17, 25–32.

Baron, J., 2000. Thinking and deciding, 3rd ed. ed. Cambridge University Press, Cambridge, UK; New York.

Bartee, E.M., 1973. A holistic view of problem solving. Manag. Sci. 20, 439–448.

Bechtel, W., Graham, G., Balota, D.A., 1998. A companion to cognitive science, Blackwell companions to philosophy; 14. Blackwell, Malden, Mass, USA.

Becker, M.C., Salvatore, P., Zirpoli, F., 2005. The impact of virtual simulation tools on problem-solving and new product development organization. Res. Policy 34, 1305–1321. doi:10.1016/j.respol.2005.03.016

Billon, S.A., 1966. Industrial Learning Curves and Forecasting. Manag. Int. Rev. 6, 65–79.

Bochm, B.W., Gray, T.E., Seewaldt, T., 1984. Prototyping versus specifying: A multiproject experiment. IEEE Trans. Softw. Eng. SE-10, 290–302.

Carlson, J.G., 1973. Cubic Learning Curves: Precision Tool for Labor Estimating. Manuf. Eng. Manag. 71, 22–25.

Carr, G.W., 1946. Peacetime cost estimating requires new learning curves. Aviation 45, 220–228.

Christensen, C.M., 2005. The innovator's dilemma: the revolutionary book that will change the way you do business. Collins Business Essentials, New York.

Christensen, C.M., Bower, J.L., 1996. Customer Power, Strategic Investment and the Failure of Leading Firms. Strateg. Manag. J. 17, 197–218. doi:10.1002/(SICI)1097-0266(199603)17:3<197::AID-SMJ804>3.0.CO;2-U

Christensen, C.M., Rosenbloom, R.S., 1995. Explaining the attacker's advantage: Technological paradigms, organizational dynamics, and the value network. Res. Policy 24, 233–257. doi:10.1016/0048-7333(93)00764-K

Clark, K.B., 1991. Product development performance: strategy, organization, and management in the world auto industry. Harvard Business School Press, Boston, Mass.

Coleman, J.S., 1966. Medical innovation; a diffusion study. Indianapolis, Bobbs-Merrill Co1966.

Conway, R.W., 1969. The manufacturing progress function. Groff Gene K 355–380.

Cooper, W.W., Charnes, A., 1954. Silhouette Functions of Short-Run Cost Behavior. Q. J. Econ. 68, 131–150.

Cyert, R.M., 1963. A behavioral theory of the firm, Prentice-Hall international series in management. Prentice-Hall, Englewood Cliffs, NJ.

David, P.A., 1970. Learning By Doing and Tariff Protection: A Reconsideration of the Case of the Ante-Bellum United States Cotton Textile Industry. J. Econ. Hist. 30, 521–601.

Dewey, J., 1938. Logic, the theory of inquiry,. New York, HHolt and Company c1938.

Duncker, K., 1945. On problem-solving., Psychological monographs, v. 58, no. 5; whole no. 270, 1945. Washington American Psychological Association.

Dutton, J.M., Thomas, A., 1984. Treating Progress Functions as a Managerial Opportunity. Acad. Manage. Rev. 9, 235. doi:10.2307/258437

Dutton, J.M., Thomas, A., 1982. Progress Functions and Production Dynamics. New York University, Graduate School of Business Administration.

Edmondson, A.C., 2002. The Local and Variegated Nature of Learning in Organizations: A Group-Level Perspective. Organ. Sci. 13, 128–146. doi: 10.1287/orsc.13.2.128.530

Edmondson, A., Moingeon, B., 1998. From Organizational Learning to the Learning Organization. Manag. Learn. 29, 5–20. doi: 10.1177/1350507698291001

Enos, J.L., 2002. Technical progress and profits: process improvements in petroleum refining. Published by Oxford University Press for Oxford Institute for Energy Studies, Oxford; New York.

Enos, J.L., 1962. Petroleum progress and profits; a history of process innovation., M.I.T. Press research monographs. Cambridge, MITPress.

Fellner, W., 1969. Specific interpretations of learning by doing. J. Econ. Theory 1, 119–140. doi:10.1016/0022-0531(69)90018-0

Franke, N., von Hippel, E., 2003. Finding commercially attractive user innovations: An exploration and test of lead user theory. Online Verfügbar Unter Httpebusiness Mit Eduresearchpapers183VonHippelLeadUser Pdf Zuletzt Geprüft Am 26, 2007.

Franke, N., von Hippel, E., Schreier, M., 2006. Finding Commercially Attractive User Innovations: A Test of Lead-User Theory*. J. Prod. Innov. Manag. 23, 301–315.

Freeman, C., Robertson, A.B., Whittaker, P.J., Curnow, R.C., Fuller, M.J.K., Hanna, S., Siddiqui, M.M., Bizot, J.-F., Wacquez, B., Fassinotti, J.-L., Coenen, R., Weber, H., Rufo, G., 1968. CHEMICAL PROCESS PLANT: INNOVATION AND THE WORLD MARKET. Natl. Inst. Econ. Rev. 29–57.

Gibson, C.M., Duncan, G.J., Gibson, C., 2002. Lessons learned: Integrating qualitative and quantitative methods in the study of the family. Unpubl. Manuscr. Durh.

Gold, B., 1981. Changing Perspectives on Size, Scale, and Teturns: An Interpretive Survey. J. Econ. Lit. 19, 5.

Hartley, K., 1965. The Learning Curve and Its Application to the Aircraft Industry. J. Ind. Econ. 13, 122–128. doi:10.2307/2097667

HaYes, R.H., 1984. Restoring our competitive edge: competing through manufacturing. Wiley, New York.

Henderson, J.M., 1971. Microeconomic theory; a mathematical approach, 2d ed. ed, Economics handbook series. New York, McGraw-Hill 1971.

Henderson, R., 1995. Of life cycles real and imaginary: The unexpectedly long old age of optical lithography. Res. Policy 24, 631–643. doi:10.1016/S0048-7333(94)00790-X

Henderson, R., 1993. Underinvestment and incompetence as responses to radical innovation: evidence from the photolithographic alignment equipment industry. RAND J. Econ. 24, 248.

Henderson, R.M., Clark, K.B., 1990. Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. Adm. Sci. Q. 9–30.

Hirschmann, W.B., 1964. Profit From the Learning Curve. Harv. Bus. Rev. 42, 125–139.

Hirsch, W.Z., 1952. Manufacturing Progress Functions. Rev. Econ. Stat. 34, 143–155. doi:10.2307/1928465

Hollander, S., 1965. The sources of increased efficiency: a study of du Pont rayon plants. Cambridge, Mass, MITPress 1965.

Iansiti, M., 1998. Technology integration: making critical choices in a dynamic world, The management of innovation and change series. Harvard Business School Press, Boston, Mass.

Kaplan, S., Tripsas, M., 2008. Thinking about technology: Applying a cognitive lens to technical change. Res. Policy 37, 790–805. doi:10.1016/j.respol.2008.02.002

Knight, K., 1963. A fast sort of country: a study of technological innovation: the evolution of digital computers.

Kolb, D.A., 1984. Experiential learning: experience as the source of learning and development. Prentice-Hall, Englewood Cliffs, NJ.

Levinthal, D.A., March, J.G., 1993. The myopia of learning. Strateg. Manag. J. 14, 95–112.

Levitt, B., March, J.G., 1988. Organizational Learning. Annu. Rev. Sociol. 14, 319–340.

Levitt, S.D., List, J.A., Syverson, C., 2013. Toward an Understanding of Learning by Doing: Evidence from an Automobile Assembly Plant. J. Polit. Econ. 121, 643–681. doi:10.1086/671137

Levy, F.K., 1965. Adaptation in the Production Process. Manag. Sci. 11, B–136. doi:10.1287/mnsc.11.6.B136

Lindblom, C.E., 1959. The Science of "Muddling Through." Public Adm. Rev. 19, 79–88. doi:10.2307/973677

Mansfield, E., 1968. Industrial research and technological innovation; an econometric analysis., [1st ed.]. ed. New York, Norton 1968.

March, J.G., 1991. Exploration and Exploitation in Organizational Learning. Organ. Sci. 2, 71–87.

Marples, D.L., 1961. The Decisions of Engineering Design. IRE Trans. Eng. Manag. EM-8, 55–71. doi:10.1109/IRET-EM.1961.5007593

Mayring, P., 1990. Einführung in die qualitative Sozialforschung: eine Anleitung zu qualitativem Denken. Psychologie-Verl-Union, München.

Mayring, P., Gläser-Zikuda, M., 2005. Die Praxis der qualitativen Inhaltsanalyse, 2., neu ausgestattete Aufl. ed, Beltz Taschenbuch. Pädagogik. Beltz, Weinheim.

Nadler, G., Smith, W.D., 1963. MANUFACTURING PROGRESS FUNCTIONS FOR TYPES OF PROCESSES. Int. J. Prod. Res. 2, 115–135. doi:10.1080/00207546308947818

Nelson, R.R., 1982. An evolutionary theory of economic change. Belknap Press of Harvard University Press, Cambridge, Mass.

Pisano, G.P., 1996. Learning-before-doing in the development of new process technology. Res. Policy 25, 1097–1119. doi:10.1016/S0048-7333(96)00896-7

Pisano, G.P., 1994. Knowledge, Integration, and the Locus of Learning: An Empirical Analysis of Process Development. Strateg. Manag. J. 15, 85–100.

Pisano, G.P., Bohmer, R.M., Edmondson, A.C., 2001. Organizational differences in rates of learning: Evidence from the adoption of minimally invasive cardiac surgery. Manag. Sci. 47, 752–768.

Rapping, L., 1965. Learning and World War II Production Functions. Rev. Econ. Stat. 47, 81–86. doi:10.2307/1924126

Rosenberg, N. comp, 1971. The economics of technological change: selected readings, Penguin modern economics readings, x249. Harmondsworth Eng Penguin.

Rosenberg, N., 1982. Inside the black box: technology and economics. Cambridge University Press, Cambridge Cambridgeshire; New York.

Rosenberg, N., 1979. Technological Interdependence in the American Economy. Technol. Cult. 20, 25. doi:10.2307/3103110

Rosenberg, N., 1976. Perspectives on technology. Cambridge University Press, Cambridge Eng; New York.

Sallee, G.P., 1974. Economic effects of propulsion system technology on existing & future transport aircraft, NASA contractor report; NASA CR-134645. American Airlines, 1974, New York.

Schön, D.A., 1983. The reflective practitioner: how professionals think in action. Basic Books, New York.

Schrage, M., 1993. The Culture(s) of PROTOTYPING. Des. Manag. J. Former Ser. 4, 55–65. doi:10.1111/j.1948-7169.1993.tb00128.x

Searle, A.D., Goody, C.S., 1945. Productivity Increases in Selected Wartime Shipping. Mon. Labor Rev. MLR 6, 1132–1142.

Shah, S., 2000. Sources and patterns of innovation in a consumer products field: Innovations in sporting equipment. Sloan Sch. Manag. Mass. Inst. Technol. Camb. MA WP-4105.

Shaw, B., 1985. The Role of the Interaction between the User and the Manufacturer in Medical Equipment Innovation. RD Manag. 15, 283–292. doi:10.1111/j.1467-9310.1985.tb00039.x

Sheshinski, E., 1967. Tests of the “Learning by Doing” Hypothesis. Rev. Econ. Stat. 49, 568–578. doi:10.2307/1928342

Siegel, S., 1957. Level of aspiration and decision making. Psychol. Rev. 64, 253–262. doi:10.1037/h0049247

Simon, H.A., 1996. The sciences of the artificial, 3rd ed. ed. MIT Press, Cambridge, Mass.

Smith, R.P., Eppinger, S.D., 1997. A predictive model of sequential iteration in engineering design. Manag. Sci. 43, 1104.

Sommer, S.C., Loch, C.H., 2004. Selectionism and Learning in Projects with Complexity and Unforeseeable Uncertainty. Manag. Sci. 50, 1334–1347. doi:10.1287/mnsc.1040.0274

Steinbruner, J.D., 1974. The cybernetic theory of decision: new dimensions of political analysis. Princeton University Press, Princeton, NJ.

Stobaugh, R.B., Townsend, P.L., 1975. Price Forecasting and Strategic Planning: The Case of Petrochemicals. J. Mark. Res. JMR 12, 19–29.

Terwiesch, C., Loch, C.H., Meyer, A.D., 2002. Exchanging Preliminary Information in Concurrent Engineering: Agenative Coordination Strategies. Organ. Sci. 13, 402–419. doi:10.1287/orsc.13.4.402.2948

Thomke, S., Bell, D.E., 2001. Sequential testing in product development. Manag. Sci. 47, 308–323.

Thomke, S., Fujimoto, T., 2000. The Effect of "Front-Loading" Problem-Solving on Product Development Performance. J. Prod. Innov. Manag. 17, 128–142.

Thomke, S.H., 2003. Experimentation matters: unlocking the potential of new technologies for innovation. Harvard Business School Press, Boston Mass.

Thomke, S.H., 1998. Managing experimentation in the design of new products. Manag. Sci. 44, 743–762.

Thomke, S.H., 1995. The economics of experimentation in the design of new products and processes (Thesis). Massachusetts Institute of Technology.

Thomke, S., von Hippel, E., Franke, R., 1998. Modes of experimentation: an innovation process—and competitive—variable. Res. Policy 27, 315–332.

Tripathy, A., Eppinger, S.D., 2011. Organizing Global Product Development for Complex Engineered Systems. Eng. Manag. IEEE Trans. On 58, 510–529. doi:10.1109/TEM.2010.2093531

Tucker, A.L., 2001. When problem solving prevents organizational learning, 2nd rev. ed, Working paper (Harvard Business School. Division of Research); 01-073. Division of Research, Harvard Business School, Boston.

Ulrich, K., 1995. The role of product architecture in the manufacturing firm. Res. Policy 24, 419–440. doi:10.1016/0048-7333(94)00775-3

Ulrich, K.T., 2012. Product design and development, 5th ed. ed. McGraw-Hill/Irwin, New York.

University of Sussex. Science Policy Research Unit, 1972. Success and failure in industrial innovation: report on Project Sappho,. London, Centre for the Study of Industrial Innovation.

Utterback, J.M., 1974. Innovation in Industry and the Diffusion of Technology. Science, New Series 183, 620–626.

Utterback, J.M., 1971. The process of innovation: A study of the origination and development of ideas for new scientific instruments. Eng. Manag. IEEE Trans. On EM-18, 124–131. doi:10.1109/TEM.1971.6448350

von Hippel, E., 2005. Democratizing innovation. MIT Press, Cambridge, Mass.

von Hippel, E., 1998. Economics of Product Development by Users: The Impact of “Sticky” Local Information. Manag. Sci. 44, 629–644. doi:10.1287/mnsc.44.5.629

von Hippel, E., 1994. “Sticky information” and the locus of problem solving: implications for innovation. Manag. Sci. 40, 429–439.

von Hippel, E., 1990. Task partitioning: An innovation process variable. Res. Policy 19, 407–418. doi:10.1016/0048-7333(90)90049-C

von Hippel, E., 1988. The sources of innovation. Oxford University Press, New York.

von Hippel, E., 1986. Lead Users: A Source of Novel Product Concepts. Manag. Sci. 32, 791–805.

von Hippel, E., 1977. The Dominant Role of the User in Semiconductor and Electronic Subassembly Process Innovation. Eng. Manag. IEEE Trans. On 60–71.

von Hippel, E.A., Tyre, M., 1995. How learning by doing is done: problem identification in novel process equipment. Res. Policy 24, 1–12.

von Hippel, E., Finkelstein, S.N., 1979. Analysis of innovation in automated clinical chemistry analyzers. Sci. Public Policy 6, 24–37.

von Hippel, E., Thomke, S., Sonnack, M., 1999. Creating Breakthroughs at 3M. Harv. Bus. Rev. 77, 47–57.

von Hippel, Tyre, M., 1995. How learning by doing is done: problem identification in novel process equipmen. Res. Policy 24, 1–12.

Wheelwright, S.C., 1992. Revolutionizing product development: quantum leaps in speed, efficiency, and quality. Free Press; Toronto, New York.

Wright, T.P., 1936. Factors Affecting the Cost of Airplanes. J. Aeronaut. Sci. Inst. Aeronaut. Sci. 3, 122–128. doi:10.2514/8.155