A MODEL OF A TECHNOLOGY ADOPTION CONTINUUM INCORPORATING RISK FACTORS

By

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Chapter 1. Introduction

1.1 Forest products industry

Primary and secondary wood products are important US industries in terms of both total production value and export income. In 1994, the value of primary wood products[1] production was estimated at $103.6 billion while furniture and fixtures (SIC 25 series), most of which contain wood, added $50 billion to national production and $3.0 billion to annual U.S. exports (USDC 1996). Yet, U.S. furniture manufacturers lost market share to furniture manufacturers in the Pacific Rim (particularly Taiwan) during the 1980s (Smith and West 1992). In 1990, the United States imported 24 percent of total U.S. wood household furniture shipments, approximately one-third from Taiwan (USDC 1992).

In Taiwan, manufacturers import logs, especially oak, from the United States, produce wood furniture and components, then ship finished wood products back to US consumers. The high transportation costs of the raw materials and the finished goods diminishes the traditional argument of low-wage foreign competition. Moreover, Taiwan is facing labor shortages and less favorable terms of trade than in the past (Smith and West 1990). Wage differentials and exchange rates alone cannot explain the significant rise in US furniture and wood products imports from countries such as Taiwan. The explanation must lie in other factors that determine a firm's ability to compete in a global wood products industry. "[T]o compete over the long run may require offering superior products, increasing product value, offering better customer service, and/or getting new products to the market place ahead of competitors; all made possible through innovative technologies" (West 1990).

1.2 Technology and competitiveness

"Technology is widely recognized as an important factor in determining the trade performance and international competitiveness of a country" (Guerrieri 1992, p. 30). Innovativeness and entrepreneurship are more powerful forces for economic growth than standard classical price competition (Landau 1992). For example, adoption of the most advanced product and process innovations, mostly imported from the

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[1] Standard Industry Classification 24 series

US, contributed significantly to the rapid rise of the Japanese electronics industry in the global marketplace (Guerrieri 1992). Landau (1992) cites studies that show that "...the comparative performance of the U.S. and Japanese labor productivity growth rates has been heavily influenced by the much higher (often doubled) rate of Japanese capital investment in a number of their industrial sectors" (p. 303). This high rate of investment fueled the rapid adoption by the Japanese of the latest available technologies. Based on these experiences, scholars maintain that one way to alleviate the competitive crisis of the United States' manufacturing industries is to leverage and expand public science and technology activities with the private sector (Gillespie 1988, Roberson and Weijo 1988). Increased emphasis on new technologies and their effective application may be particularly important to the wood furniture industry since "[i]n ... older [industries] faced with new competitors, the bases of competition are more likely to be product innovation, advanced technology and quality" (Whitney et al. 1988, p. 204).

1.3 Technology

To find a single, definitive answer to the question, "what is technology?" is impossible. Technology can mean different things to different people. For some people, technology consists of "direct problem solving inventions" (Leavitt 1965, cited in Shrivastava and Souder 1987). For others, technologies are things that may be easily described and enumerated such as "tolls, techniques, procedures, and/or the legal titles thereto, used to accomplish some desired human purpose" (Reisman 1989). Still others consider technology to include all of the above mentioned definitions as well as the more nebulous components of 'know how,' or proprietary information (Coursey and Bozeman 1992); or the knowledge of activities, equipment, machines, tools, methods, processes, layout arrangements or patterns (Shrivastava and Souder 1987); i.e. technology includes knowledge or ideas as well as physical products (Gibson and Smilor 1991).

Throughout this research, a broad definition of technology will be used: technology refers to the physical devices, processes, 'know how', activities, methods, and concepts which are used to accomplish some purpose put forth by people. Manufacturing technology refers to the physical devices, processes, 'know how', activities, methods, and concepts which are used in the design and production of an item or items. New technology refers to technology that is new to a firm. Technology that has been adopted by other firms in the same industry or other industries is not excluded from the potential members of a set of new technologies.

1.4 Technology adoption/rejection decision process

As discussed above, technology can be broadly defined to include a wide range of products and approaches. For example, technology may deal with new instruments for testing for disease; it may deal with a new way of tracking inventory costs; it may deal with new computer graphics used in advertising. Technology is not limited to one discipline or one application, nor is it limited to one point in time. Therefore, the technology adoption decision should not be viewed as a simple, instantaneous, one-time only, go/no-go decision.

Scholars in the social sciences have described the technology adoption decision process as a series of consecutive steps (e.g., Muth and Hendee 1980, Rogers 1983). Rogers (1983) describes the innovation-decision process as:

1. Knowledge - individual first becomes aware of an innovation's existence and gains some understanding of how it functions;

2. Persuasion - individual forms a favorable or unfavorable opinion of the innovation;

3. Decision - individual engages in activities that lead to adoption or rejection of the innovation;

4. Implementation - innovation is put to use; and,

5. Confirmation - confirmation of an innovation adoption decision is sought; the decision may be reversed at this point if warranted.

Muth and Hendee (1980) also describe the adoption decision process using five steps. Their model consists of:

1. Awareness - individual is first exposed to the innovation but technical details need not be included;

2. Interest - individual seeks more information about the innovation and considers if and how it applies to him/her and his/her firm;

3. Evaluation - individual makes a mental application of the innovation, weighing benefits, costs, complexity, trialability, etc.;

4. Trial - individual asks for a demonstration of the innovation on a limited scale to test and validate the workability of the innovation, thus reducing risk; and,

5. Adoption/rejection - individual decides either to use the innovation or reject it.

While the terminology may be different, several of the phases appear to be very similar between the two descriptions. However, to get a more complete picture of the adoption/rejection decision process, the two models could be combined:

1. Knowledge/Awareness - individual first becomes aware of an innovation's existence and gains some understanding of how it functions but technical details need not be included;

2. Interest - individual seeks more information about the innovation and considers if and how it applies to him/her and his/her firm;

3. Evaluation/Trial - individual makes a mental application of the innovation, weighing benefits, costs, complexity, trialability, etc., and asks for a demonstration of the innovation on a limited scale to test and validate the workability of the innovation, thus reducing risk;

4. Persuasion - individual forms a favorable or unfavorable opinion of the innovation;

5. Adoption/rejection decision - individual engages in activities that lead to adoption or rejection of the innovation;

6. Implementation - innovation is put to use; and,

7. Confirmation - confirmation of an innovation adoption decision is sought; the decision may be reversed at this point if warranted.

1.5 The adoption continuum

It is the premise of this research that technology adoption is not a dichotomous decision. However, most published research in this area tends to characterize it as such. Technology adoption would be better thought of as a continuum with forces pushing towards adoption and forces pushing against adoption as shown in Figure 1.1.

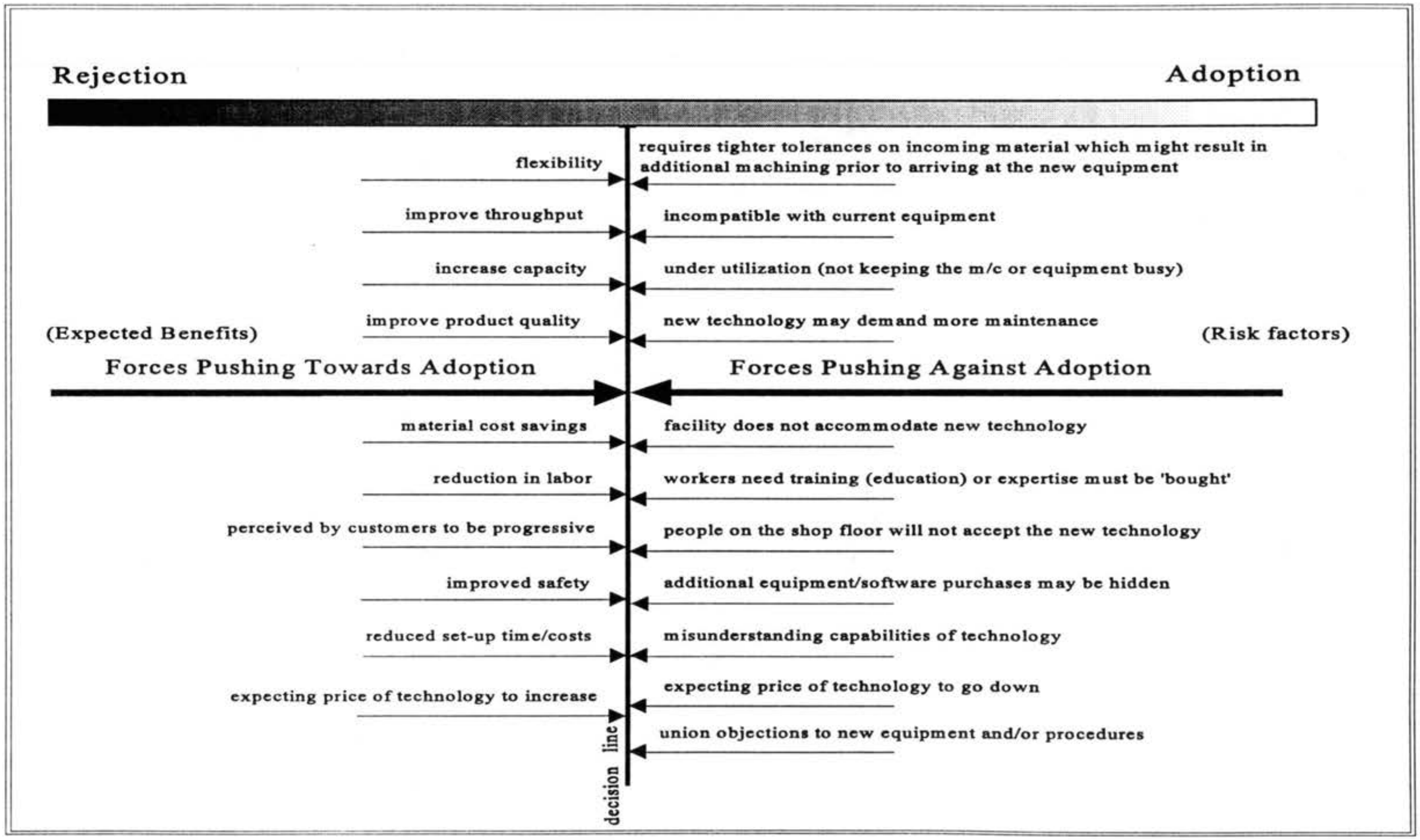

Figure 1.1. Technology adoption continuum and some of the possible forces that might act on the decision line

A firm's position along the continuum is determined by the strength of various forces acting within and upon the firm. These forces contribute varying amounts of influence on the adoption decision during different phases of the decision process. If the decision maker focuses mainly on those forces pushing against adoption, he/she may be leaning towards non-adoption, but not to the point of total rejection. Similarly, if the decision maker feels that those forces pushing towards adoption outweigh those pushing against adoption, he/she may be leaning towards adoption but not to the point of actually acquiring the technology or implementing it.

Furthermore, a firm may choose not to adopt a technology at one point in time only to decide to adopt the technology later on. As Gatignon and Robertson (1989) note, it would not be reasonable to classify organizations that are still in the process of evaluating whether or not they should adopt a certain technology as having made a decision to reject the innovation. In fact, as a technology advances through its life cycle, it is expected that firms at the non-adoption end of the spectrum would move towards the adoption end of the spectrum.

1.6 Expected benefits and risk factors

Forces pushing towards adoption of a new technology are usually *expected benefits* to be gained by adopting the particular technology being considered. The primary exception to this characterization is an expected increase in the price of acquiring the technology in the future. Examples of benefits associated with many types of technology adoption are abundant in the current literature (e.g., Meredith 1987, Wiarda 1988, Lefebvre et al. 1991, King and Ramamurthy 1992, Dimnik and Johnston 1993).

Forces pushing against technology adoption have been suggested in the literature, but they have rarely been investigated in any formal studies. In this research, forces pushing against technology adoption will be called *risk factors*. Risk factors are typically aggregated into a single cost category or into a regulatory compliance category (e.g., Lefebvre et al. 1991, King and Ramamurthy 1992, Moore 1994, Parente and Prescott 1994). However, this gives very little insight into factors that contribute to the resistance of technology adoption.

Scholars suggest that many of the factors that traditionally push towards technology adoption (expected benefits) may not have the impact that they have had before (Doz 1987). For example, in some cases, new technology has been so successful at reducing manufacturing costs that these costs comprise only a small portion of the total costs. Further reductions in manufacturing costs would not have the same impact that they had before, and therefore may not drive the adoption decision with the same strength as they might have before. Reductions in the strength of factors pushing against technology adoption (risk factors) could become very important in the adoption of new technologies.

1.7 Characteristics

There are other issues that appear to impact technology adoption while not actively forcing or pushing towards or against adoption. They describe the firm, the primary decision-maker, or the competitive environment in which the firm operates. These issues will be called *characteristics* and contribute to a firm's willingness to innovate and ability to innovate. For example, firm size has been found to be positively related to the adoption of new manufacturing technologies (e.g., Rahm and Huffman 1984, Keefe 1991, West and Sinclair 1992). There may be many reasons why larger firms are more likely than smaller firms to adopt new technologies, but being large is not one of them. Larger firms may have deeper capital resources so the initial capital investment required for technology adoption may not be as restrictive as it may be for smaller firms. Larger firms might have a larger workforce so the absences experienced when one or two people attend training classes for new technologies may not have the impact that they would have in a smaller firm. Larger firms may employ more technical experts than smaller firms thus reducing the uncertainty of expected performance of a new technology. Early adopters of new technologies may be characterized by large firms, but being large does not (in itself) explain adoption behavior.

Many characteristics have been suggested in the adoption literature and these are discussed in greater detail in upcoming sections. Few of these characteristics have been found to have the same effect on adoption behavior across all industries. Furthermore, these characteristics have rarely been investigated with respect to rejection behavior.

1.8 Problem statement

Implementation of new manufacturing technologies has been suggested as a source of improving competitiveness through higher quality, lower costs and increased flexibility (Whitney et al. 1988, West 1990, Hoff et al. 1997). If adopting new technologies is one of the answers and if wood products manufacturers are not adopting many of these new technologies as reported in the current literature, one question is "why not?".

Answers to the question of why process improvements that offer the advantages of reduced costs, improved quality, increased flexibility and improved safety in the work environment are *not* adopted should be of particular value to developers of technologies aimed at improving efficiency and quality. What are the forces pushing against technology adoption? These forces or risk factors had not been identified or included in technology adoption models.

Prior to this research, no model existed that considered characteristics and risk factors and related them to their effects in the adoption/rejection decision process. Furthermore, there was no generic mechanism to test such a model and see how it fits a particular segment of an industry (e.g., regional segmentation may be appropriate in wood products manufacturing).

1.8.1 Objectives

This research developed a technology adoption model, identified characteristics and risk factors that impact the technology adoption/rejection decision, integrated them explicitly into a technology adoption model, and tested that model.

1. Developed a model of technology adoption and rejection that included characteristics and risk factors and described their impacts on the adoption/rejection decision.

2. Determined characteristics that may differentiate between firms that adopt a technology or set of technologies (adopters) and firms that consider adopting that technology or set of technologies but who choose not to adopt (rejecters).

3. Determined risk factors that may differentiate between technology adopters and rejecters.

4. Analyzed the ability of the characteristics found in objective 2 and the risk factors found in objective 3 to explain variance in levels of technology adoption and rejection by applying the model to the wood products industry in the South Central United States.

5. Modified the model as necessary to incorporate what was learned in objective 4.

1.9 Significance

This research extended the body of knowledge concerned with technology rejection and the much larger body of knowledge concerned with technology adoption. The model developed in this research extended previous models by considering risk factors as well as characteristics and their effects on the technology adoption decision. Earlier research was also extended by recognizing a continuum of outcome possibilities between adoption of a technology and rejection of that technology.

Chapter 2. Literature Review

Technology adoption literature spans a wide range of fields of study. From agricultural economics and industrial economics to psychology and sociology, who adopts new technology and why are questions that warrant investigation. Various studies have developed technology adoption models based on characteristics of the firm, characteristics of the primary decision maker, characteristics of the supply-side industry, or characteristics of the adopter industry. "Although the applicability of findings in one sector [of the economy] to those in another is clearly problematic, concentration of the research focus can help to identify and isolate factors that clarify the nature of the phenomenon in that sector and, at the very least, can be helpful in suggesting hypotheses that may be generalizable beyond that sector and tested in others" (Kimberly and Evanisko 1981, p. 691). Other studies have attempted to identify the objectives firms are trying to meet when they adopt and implement new technologies while further studies have attempted to determine if those objectives were met and if not, why not.

Technology adoption literature crosses many academic and industrial boundaries. For example, researchers cited here hail from a variety of disciplines including agriculture, marketing, sociology, geography, management and industrial engineering. The industries studied include agri-business, sales, health care and manufacturing. As noted above, results from any one of these studies should not be considered definitive for all industries. However, by considering this diversity of studies, factors that may not have been considered in previous manufacturing-related studies may come into focus.

This review of the current literature begins with a brief discussion on the role time plays in various studies. Factors that have been proposed as positive and negative influences on technology adoption are then examined. The proposed positive factors discussed here include: characteristics of adopting firms, characteristics of primary decision makers, characteristics of the supply-side industry and the adopter industry, characteristics of the technology itself, expected benefits as a driving force behind technology adoption, and serendipity's role in the acquisition and implementation of new technologies. Next, results of studies that examine post-adoption effectiveness (confirmation step) are summarized. The review concludes with a look at earlier technology adoption studies directed at the wood products industry and a short run-down of some of the mathematical approaches that have been used to model various aspects of technology adoption.

2.1 The effect of time

Time plays an important role in the study of technology adoption. Time is considered with respect to an innovation's product life cycle and is reflected in adopter categories. Rates of adoption, diffusion, or knowledge acquisition also reflect time considerations. Also, since the adoption decision is not instantaneous, the technology adoption decision process takes place over time.

Adopter categories are used to identify early adopters from late adopters. What percentage of adopters are considered early adopters? What percentage of adopters are considered late adopters? The use of a percentage to categorize is arbitrary and chosen either because of convenience to the researcher or because empirical data seems to dictate an obvious breaking point. The most commonly used adopter categories appear to be those described by Rogers (1983). Rogers found evidence that adopter distributions seem to approach normal in eight different studies. Therefore, each adopter category is represented as an area under the normal curve. These adopter categories are depicted in Figure 2.1.

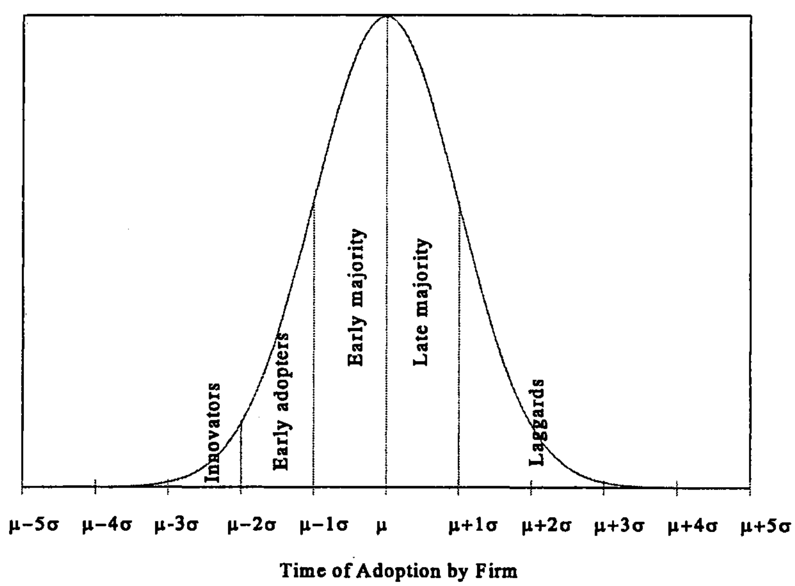

Figure 2.1. Adopter categories (source: Rogers 1983)

In his description of adopter categories, Rogers (1983) rounds the percentages associated with each category to the nearest one half of one percent. The first 2.5 percent to adopt an innovation are considered innovators and are described as venturesome risk-takers. The next 13.5 percent to adopt an innovation are considered early adopters and are described as respectable opinion leaders. The next 34 percent to adopt are referred to as the early majority and they are described as deliberate but cautious. The next 34 percent to adopt are called the late majority and they are described as skeptical. The final 16 percent to adopt are called laggards and are typically described as traditional. One assumption with this categorization scheme is that 100 percent of all potential adopters will adopt the innovation eventually.

Many studies in technology adoption refer to "early adopters." This term does not always appear to reflect the single category in the five category system described by Rogers. In fact, it appears that the term "early adopters" often refers to Rogers' innovators, early adopters and at least some portion of the early majority.

Much of the technology adoption research attempts to identify common characteristics of those people/firms who adopt new technologies relatively early in the technology's life cycle (early adopters) (e.g., Kimberly and Evanisko 1981, Feder and Slade 1984, Rahm and Huffman 1984, Wozniak 1984, Robertson and Gatignon 1986, Harper et al. 1990, McIntosh et al. 1990, Lin 1991, Baker 1992, Saha et al. 1994). In general, there appear to be some characteristics common to early adopters regardless of the type of technology being considered or the industry within which the adopters operate. However, some characteristics appear to be indicative of early adoption in some studies, but they do not appear to have any significant impact on adoption behavior in other studies. Recognizing factors that characterize early adopters of technologies could provide some insight into the competitiveness of the firm since early adoption is often related to competitive advantage (Landau 1992, Dröge et al. 1994, Stenbacka and Tombak 1994, Zepeda 1994).

2.2 Characteristics of the firm

During the following discussions regarding adopter characteristics associated with the firm, the primary decision maker, or the industry, it should be noted that the identified characteristics may reflect some effect of the marketing strategies of the developers of the technologies. Robertson and Gatignon (1986) warn that "research which discovers that innovators are, for example, large firms may only be confirming the market segment selection practice of the marketer" (p. 6). Also, a summary of the results of the empirical studies that are included in these discussions is given at the end of the chapter in Table 2.1.

2.2.1 Firm size

Throughout the technology adoption literature, several different measures were used to quantify the characteristic of "firm size." In the agricultural literature, farm size typically referred to the number of acres currently farmed (e.g., Feder and Slade 1984, Rahm and Huffman 1984, McIntosh et al. 1990), or the number of animals in the herd (e.g., Saha et al. 1994). In their work on technology adoption in hospitals, Kimberly and Evanisko (1981) found that high correlations existed among the following four variables: number of beds, total assets, total number of employees and number of full-time equivalent employees[2]; therefore, they used the most dominant measure among hospital researchers, number of beds, to represent firm size. In the marketing literature, firm size often referred to total sales (e.g., Baker 1992, Levin et al. 1992), and researchers in management and manufacturing often used number of employees as a measure of firm size (e.g., Wiarda 1987, West and Sinclair 1992, Knudsen et al. 1994).

In most studies, firm size, however it was measured, was positively related to the likelihood of adoption of new technologies (e.g., Kimberly and Evanisko 1981, Feder and Slade 1984, Rahm and Huffman 1984, Wozniak 1984, Wiarda 1987, Hodges and Cubbage 1990, McIntosh et al. 1990, Keefe 1991, Lefebvre et al. 1991, Lin 1991, Baker 1992, West and Sinclair 1992, Goodwin and Schroeder 1994, Saha et al. 1994). This positive relationship most frequently is "attributed to economies of scale, which enhance the feasibility of adoption" (Kimberly and Evanisko 1981, p. 698). Also, smaller operations may have tighter financial constraints and lack the expertise (or resources necessary to acquire expertise) for implementing and maintaining new technologies (Baker 1992) while larger firms are more likely to have the skills and human resources needed to understand, implement, and manage new technologies (Meredith 1987).

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[2]Number of full-time employees plus one half of the number of part-time employees.

Although smaller firms tend to have less access to capital and information than large firms, some researchers suggest that smaller firms have some advantage in the adoption and implementation of new technology (e.g., Meredith 1987, Harvey et al. 1992, Knudsen et al. 1994). Large firms are less able to adapt quickly to new methods of production than smaller firms (Knudsen et al. 1994). Also, Knudsen et al. (1994) suggest that small plants are less likely to be unionized and thus, technologies that require cross-functional training may be more readily adopted in smaller plants. While agreeing that firm size appears to have some effect on technology adoption, Keefe (1991) has a different take on the influence of unions and the interaction of unions and firm size. Keefe (1991) concluded that "union status has no apparent effect on the use of advanced manufacturing technology" (p. 273). In fact, he found that among his sample of machinery manufacturing establishments, unionized plants "...are more likely than nonunion plants to be using advanced technology -- not, however, because they are unionized, but primarily because they are larger and more likely to operate on shift work" (p. 273). Martin (1994) also found a positive correlation between the number of shifts operating in a plant and technology adoption.

Meredith (1987) argues that smaller firms seem better able to capitalize on the benefits of new manufacturing technologies. "Furthermore, the new technologies seem to offer the types of benefits that small firms are already used to competing with: fast customer response, quick production, more customization, greater variety, and so on" (Meredith 1987, p. 257). Evidence in Wiarda's (1987) suggests that "...once a smaller establishment adopted a technology, it tended to make much more of a commitment to its use than did larger plants" (p. 128). One explanation proposed for this higher level of commitment is that the relatively fewer bureaucratic processes typically associated with smaller firms impose fewer constraints on the adoption and implementation of new technologies.

When investigating the adoption and diffusion of optical scanners in grocery stores, Levin et al. (1992) found that there appeared to be a minimum store size that made the adoption of the technology profitable. The more a store exceeded that minimum size (measured in dollars), the more likely it was to adopt the optical scanners. However, the companies that operated more stores in the market area under study were slower to diffuse the use of optical scanners throughout those stores. So, does this mean that multi-facility operations are slower to diffuse new technology than single facility operations? Not necessarily. West and

Sinclair (1992) found that larger wood household furniture manufacturers with multiple manufacturing plants, higher production volumes and better access to capital markets tend to adopt more innovative manufacturing technologies.

Even though most studies found firm size to be significant with respect to likelihood of adoption, some studies did not (e.g., Harper et al. 1990). Harper et al.'s (1990) agricultural study concluded that "farm size (total acreage) ... was not found to significantly influence adoption" of insect sweep nets or treatment thresholds in rice production (p. 1002). There are a couple of points that need to be made here: 1) the Harper model did not include total acreage of the entire farm; it only included the number of fields (and acreage) planted in rice and 2) the technology being studied was a relatively inexpensive technology and in fact, was somewhat labor-intensive.

Within a more "consultant" type of industry, Hodges and Cubbage (1990) found that as the number of landowners assisted increased, adoption of new technologies by technical assistance foresters increased.

2.2.2 Centralization of decision making

Kimberly and Evanisko (1981) state that "[a]lthough the relationship between centralization and adoption of innovation has been found to be positive in some cases, in others the relationship has been negative. Rarely, if ever, has it been found to make no difference whatsoever" (p. 697). They go on to hypothesize that the type of influence centralization exerts on the adoption decision may depend on the nature of the relationship between the innovation and the key decision makers as well as on the type of innovation. Gatignon and Robertson (1989) suggest that inconsistent findings regarding the influence of centralization on adoption behavior might be due to the type of innovation.

McIntosh et al. (1990) claim that "[i]n most organizations, the concentration of authority correlates negatively with flexibility and innovativeness" (p. 852). They go on to explain that this concept is mainly applicable to innovations concerned with economic gains. When it comes to innovations/technologies primarily concerned with more environmental issues or "pet projects" of the decision maker, centralization tends to be positively associated with the adoption of those technologies.

In their study of optical scanner use in grocery stores, Levin et al. (1992) found that "smaller firms with fewer stores ... should make decisions more quickly, operate more flexibly and with relatively low overhead face lower adjustment costs, resulting in faster diffusion rates" (p. 347). While they do not explicitly attribute this result to a more centralized decision making function in firms with fewer stores, this is one possible explanation.

Kimberly and Evanisko (1981) found that centralized decision making was negatively correlated with adoption when dealing with *technological innovations* directly related to the diagnosis and treatment of disease and positively correlated with the adoption of administrative technologies.

The degree of vertical integration within a firm may have some effect on the likelihood of technology adoption. Higher degrees of vertical integration are associated with increased rates of adoption (Lane 1991).

2.2.3 Participation in decision making by top management

Kimberly and Evanisko (1981) propose that "[t]he decision to adopt an innovation will be affected not only by the performance characteristics of the innovation but by the way in which various key actors in the organizational system assess its likely impact on them and their prerogatives" (p. 709-710). If an industry is characterized by management leaders who support the idea of adopting new technologies, then diffusion is greatly facilitated (Shrivistava and Souder 1987). In small companies, chief executive officers (CEOs) appear to have the greatest individual influence on the initial decision to adopt new technology (Lefebvre et al. 1991). Yet, a manager's active participation in the decision process had more to do with the effectiveness of an adopted technology than with the yes/no adoption decision in Baker's study (1992).

Somewhat related to this topic is the idea of a "champion." A champion is a technology advocate who tries to convince other people in the organization to accept their ideas through a process of persuasion, salesmanship, and negotiation in which personal credibility and political support carry as much, or more, weight than financial or strategic criteria (Langley and Truax 1994). The role of a top manager as a champion may be especially important in the technology adoption decisions of small firms (Meredith 1987). Dimnik and Johnston (1993) suggest that manufacturing managers fill the role of a champion in two ways. First, they recognize a match between new innovations and their own operations and relate this match to the strategies of the firm (familiarization). Second, they convince others in their firm of the benefits of new technologies (promotion). Familiarization and promotion parallel knowledge and persuasion in Rogers' model with respect to the behaviors associated with the innovation champion alone (Dimnik and Johnston 1993).

2.2.4 Planning horizon

It has been suggested that firms with shorter *planning horizons* (e.g., those renting space) seem to be more risk averse and therefore less likely to adopt new technology than those with longer planning horizons (Rahm and Huffman 1984). The definity of this statement is suspect though. The effect of the planning horizon on the likelihood of adoption appears to be dependent on the nature and cost of the technology being considered. McIntosh et al. (1990) claim that firms with longer planning horizons are more likely to adopt *value rational innovations*[3] than firms with shorter planning horizons, and that firms with shorter planning horizons are more likely to adopt *instrumentally rational technology*[4] than firms with longer planning horizons. Meredith (1987) contends that firms with longer term perspectives may be a better fit for technologies that are "flexible, computerized systems that are meant to be reprogrammed and used over an extended time frame" (p. 256)[5].

Geroski's (1991) research indicates that longer time horizons should be considered when faced with technology adoption decisions because most innovations have "...a long run effect (requiring perhaps as long as 10-15 years to realise (sic)) on productivity growth that may be as much as ten times the size of their short run effect" (p. 1449). Likewise, capital expenditures justified on the basis of long-term returns may result in different adoption decisions from those based on short-term returns (Skinner 1984).

Despite conflicting results regarding the effect of the planning horizon on the adoption decision, identification of long- and short-range objectives is necessary for effective technology transfer when moving technology from the research phase to operations (Achenbach 1987).

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[3]Value rational technology: Technologies that do not "...necessarily increase efficiency or effectiveness, but may instead promote values of craftsmanship or resource preservation; certain types of soil conservation practices reflect this form of rationality" (McIntosh et al. 1990, p. 848).

[4]Instrumental rational technology: Technology that "tends to increase efficiency and effectiveness", or could prove "highly profitable" (McIntosh et al. 1990, pp. 848-849).

[5]Meredith (1987) argues that small firms are likely to have long term perspectives while Harvey et al. (1992) argue that small firms are more likely to have short term objectives.

2.2.5 Age of firm

West (1990) cites previous research studies by Davies (1979) and Ozanne and Churchill (1971) that found that younger companies were more likely to innovate than older, established ones. However, her research indicated that this relationship did not appear to hold true for the furniture industry with a mean age of 68 years for innovators and 60 years for non-innovators (West 1990). This finding suggests that age is not a good determinant of innovativeness (West and Sinclair 1992). Likewise, Kimberly and Evanisko (1981) found evidence to suggest that high adopting hospitals tend to be older when faced with technological innovations (those dealing with the diagnosis or treatment of disease). Also, Oakey and O'Farrell (1992) found that newer firms that adopted CNC machinery appeared to have more problems with CNC introduction than older firms that adopted CNC machinery.

2.2.6 Functional differentiation

Functional differentiation refers to the extent to which an organization is divided into a number of subunits with different purposes. It has been suggested that organizations that are highly differentiated functionally are more likely to be adopters of technological innovations in the health care industry (Kimberly and Evanisko 1981). In addition, one study showed that division of labor appeared to have a positive effect on the likelihood of adopting soil conservation practices (McIntosh et al. 1990).

2.2.7 Technical expertise

In West's (1990) study, innovative firms were found to employ a significantly greater number of manufacturing engineers than non-innovative firms. This was not a startling finding since engineers often can understanding the complexities of new technologies and therefore, reduce the risk of adopting and implementing them (West 1990, West and Sinclair 1991, West and Sinclair 1992). What is surprising is the absence of this variable in other manufacturing technology adoption studies. Some studies might have eliminated this variable because there may be a high correlation between the number of engineers employed and firm size. West and Sinclair (1991) found that such a correlation existed within firms in the wood household furniture industry. Other studies may have considered the number of already adopted technologies to be a surrogate measure for technical expertise. However, utilization of earlier competing technologies could reduce the likelihood of adopting new technologies (Lane 1991).

2.2.8 Management structure

Management structures that are conducive to innovativeness tend to be flexible and organic in nature (Kanter 1983, Utterback 1987, Holt 1991, Martin 1994). Kanter (1983) suggests that those organizations that will be successfully managing technical change "...will be, above all, flexible; they will need to be able to bring particular resources together quickly, on the basis of short-term recognition of new requirements and the necessary capacities to deal with them" (p. 42). Martin (1994) echoes the need for flexibility in the management structure. As an innovation or new technology moves into an operational setting, "[t]he project team and its complement now cut across management functions and the requirements of ongoing product lines" (p. 277).

2.2.9 Market share

Firms with larger market share were found to be more likely to adopt optical scanners in grocery stores sooner than firms with smaller market shares, but they do not appear to diffuse this innovation more quickly throughout the firm than their smaller rivals (Levin et al. 1992). Besley and Case (1993) point out that "[a]dopters with market power will care about adoption by others if adopting early implies some advantage in market power" (p. 399). One exception to these trends is the case where one firm monopolizes the market (Gatignon and Robertson 1989).

2.3 Characteristics of the primary decision maker

2.3.1 Education of the decision maker

The educational level of the primary decision maker within the firm also appears to have some influence on whether or not new technologies are adopted. Kimberly and Evanisko (1981) point out that the "educational background of leaders has been found consistently to be related to adoption behavior in previous research. The higher the level of education, the more receptive an individual has been found to be to innovation" (p. 696). Feder and Slade (1984) argue that farmers with higher education levels are able to decipher and interpret information better. Similarly, Wozniak (1984) claims that producers with more education should be "more efficient in evaluating and interpreting information about innovations than those with less education" (p.72). Using this line of logic and the results of empirical studies, many researchers have concluded that producers with more education are more likely to be adopters than operators with less education (e.g., Kimberly and Evanisko 1981, Feder and Slade 1984, Wozniak 1984, Lin 1991, Goodwin and Schroeder 1994, Saha et al. 1994). One notable exception lies in Baker's 1992 study where the manager's education was not found to be significant in the computer adoption decision, but it was definitely significant with respect to post-adoption computer effectiveness.

Participation in seminars and other educational programs, whether they are provided through government agencies or private agencies appears to be positively related to the likelihood of technology adoption for agricultural industries (e.g., Feder and Slade 1984, Wozniak 1984, Goodwin and Schroeder 1994).

Other researchers stress that a more accurate conclusion would be that increased education is more likely to increase the probability of farmers/producers making the "correct" adoption decision (Rahm and Huffman 1984, Harper et al. 1990, McIntosh et al. 1990). Rahm and Huffman (1984) and Harper et al. (1990) consider the economically correct decision while McIntosh et al. (1990) focuses on the environmentally correct decision (Note: these could be one and the same if the planning horizon is extended to the point where environmental sustainability is vital to the economic survival of the firm). Despite discovering that education has a significant negative effect on the adoption of sweep nets and treatment thresholds in the eradication of the rice stink bug, Harper et al. (1990) acknowledge that "[a] possible explanation for this behavior is that the higher educated producers perceive a greater return to their management and labor time elsewhere in their operation, and/or the physical aspects of using a sweep net are unexciting or menial to such producers" (p. 1001). Again, this is related to increased ability to conceptualize the results of actions being contemplated.

An improved ability to predict and comprehend the effects of adopting technological improvements is enhanced by education (Wozniak 1984). McIntosh et al. (1990) suggest that higher levels of education also increase the probability of adoption of techniques for environmental sustainability such as improved soil conservation practices. Thus it appears that the influence of the education of the primary decision maker on adoption decisions is dependent on the type of technology, the projected returns from the technology and the "glamour" of the technology. It also appears that this influence is not necessarily always positive or negative with respect to the likelihood of adoption, but it does tend to be positively related to making the best decision for the long-term viability of the firm. In addition, there is general consensus that higher education results in a more efficient evaluation of the adoption decision (Feder and Slade 1984, Rahm and Huffman 1984, Wozniak 1984, Harper et al. 1990, Saha et al. 1994).

If the level of education is important to technology adoption behavior, would it not make sense to consider the content of the decision maker's education? When formulating their study, Kimberly and Evanisko (1981) were concerned that not only did the level of education of hospital administrators vary widely, but the substance of their educations varied widely. After testing for a difference in adoption behavior between hospital administrators who had been trained specifically in administration and those who had not, no significant differences were found. While most agricultural studies include the number of years of schooling as a possible factor in explaining adoption behavior but not the type of education, Rahm and Huffman (1984) considered the effects of high school vocational training and completion of a college agriculture major on the efficiency of the adoption decision[6]. Neither vocational training in high school or completion of agricultural majors in college had significant effects on adoption decision efficiency.

While neither one of these studies prove that the type of education the primary decision maker receives significantly affects adoption behavior, the impact of technical expertise within a firm seems to suggest that a more technical background may positively influence the probability of adoption of new technologies in manufacturing environments. Furthermore, after observing twelve large-scale advanced manufacturing firms, Skinner (1984) suggests that the financial background of many top managers impedes investment in new technology. So, while nothing can be said conclusively, it appears that the type of education a manager receives may have more of an impact when considering technology adoption in the manufacturing arena than it does in other industries.

[6]Efficiency of the adoption decision was measured as the absolute difference between the actual adoption decision D_i ($D_i = 1$ if adopted and replaces old technology; $D_i = 0$ if old technology continues) and the probability of adopting the new technology based on estimated effects of variables, P_i. Efficient adoption decisions imply adopting new technology when P_i is large or non-adoption when P_i is small.

2.3.2 Age of the decision maker

The age of the farm manager did not prove to be significant in the adoption of low-technology sweep nets to eradicate the rice stink bug (Harper et al. 1990). Regarding higher technology, Baker's 1992 study of computer use in New Mexico's non-farm agribusinesses showed that the age of the manager did not appear to affect computer adoption. However, the age of the manager *did* appear to have some impact on the effective implementation of computers once they were adopted.

Lin (1991) proposes that when it comes to family-owned farms, the younger the household head is, the better is his or her education. Given that Lin's study found a strong positive relationship between education and adoption behavior, it would seem reasonable to expect that younger decision makers would be more likely to adopt the technology in question.

2.3.3 Technological experience or tenure of the primary decision maker

Familiarity with manufacturing technologies provides a basis for the rational contemplation of the technology adoption decision (Lefebvre et al. 1991). It would be reasonable to expect that experience with other new technologies would result in much the same influences as education since learning by doing is a form of education. However, the literature suggests that earlier experiences with new technologies does not have a clear cut influence on the likelihood of later technology adoption decisions. One point that is difficult to deny, though, is that the prior track record of the firm's managers is particularly important when trying to secure funding for the innovation (Langley and Truax 1994).

Considering the instance where an operator has had experience with then-new technologies, there appear to be two major sources of variation in the type of influence earlier experiences with new technologies have on the adoption of later technology: the effectiveness of the earlier technology and the rate of changes (improvements, enhancements) to the later technologies. Oakey and O'Farrell (1992) suggest that a major determinant of subsequent acquisition of additional CNC equipment is the financial success of the first CNC machine placed in production. Also, foresters already practicing intensive land management were found to be more likely to adopt new management practices (Hodges and Cubbage 1990). Harper et al. (1990) found that a farm manager's likelihood of adoption of pest management technologies is affected by his/her previous experience with new technologies in the production of rice.

Similarly, McIntosh et al.(1990) found a positive relationship between the use of modern management practices (such as forward contracting, computer-based record keeping, etc.) and the likelihood of adopting soil conservation practices.

Goodwin and Schroeder (1994) found that adoption of forward-pricing methods for certain grain crops decreased with increased experience without specifically considering experience with other new technologies. Likewise, increased experience in agriculture (measure in years) demonstrated a positive effect on the likelihood of adoption in Lin's (1991) study on the adoption of hybrid rice in China.

Again, the causality of this factor is difficult to state with certainty. "Does the level of technological experience influence the adoption decision process, or is it the other way around, or even a combination of both?" (Lefebvre et al. 1991).

2.3.4 Information preferences

The types, sources, and volume of information to which the primary decision maker has access appear to have some effect on adoption decisions. "[P]roducers' choices are significantly affected by their exposure to information about the new technology" (Saha et al. 1994, p. 837). Empirical evidence suggests that those producers who have better access to information are more likely to adopt new technologies faster (e.g., Feder and Slade 1984, Langley and Truax 1994).

The types of information available to the decision maker are important as well. For example, Gatignon and Robertson (1989) found that negative information outweighs positive information in the consumer's decision process. Therefore, individuals with a more tolerant attitude toward negative information are more receptive to innovations.

Increases in information from sources outside the organization appear to increase the probability of adoption. Decision-makers who may be characterized as *cosmopolitans* are more likely to be exposed to new developments in their industry and related industries (Kimberly and Evanisko 1981, Robertson and Gatignon 1986, West and Sinclair 1992). This type of integration with external information has proven to be a positive factor in the adoption of technologies when the adopting unit is an individual (Kimberly and Evanisko 1981). Probability of adoption of new or improved land management practices by individual foresters increased with increased communication with foresters outside the individual forester's organization (Hodges and Cubbage 1990).

Gatignon and Robertson (1989) found that "... individuals with greater access to relevant personal information sources are in a better position to evaluate and adopt innovations" (p. 39). Direct sources of information such as equipment shows and contact with representatives of equipment manufacturers appear to have a positive effect on the adoption of manufacturing technologies (West and Sinclair 1992). Of course, information from neutral sources may be perceived as more valuable than information from producers of the technology. For example, information obtained from agricultural extension sources about the use of new products and procedures is sometimes regarded as more credible or reliable than information from supplying firms (Wozniak 1984). Attendance at extension service sponsored field days, demonstrations and seminars has been found to affect adoption decisions (e.g., Harper et al. 1990). Increased use of university sources of information increased the probability of land management change in a study of technical assistance foresters (Hodges and Cubbage 1990).

2.4 Characteristics of the supply-side industry

In much of the technology adoption literature, the focus is on the characteristics of the adopter (firm or individual) or the adopter industry with very little focus on the characteristics of the technology supplier or the supplier industry. The works of Robertson and Gatignon (1986) and Gatignon and Robertson (1989) are some of the very few works that even mention the effect of supply-side characteristics on the adoption of new technologies. "Indeed, to a very large extent, most research seems to assume that there is only one firm supplying the innovation--a condition that rarely holds" (Robertson and Gatignon 1986, p. 2). Suppliers affect technology adoption and rates of adoption and diffusion when they determine the characteristics of the innovation and set the price of the innovation (Robertson and Gatignon 1986). In addition, there are other characteristics of the supplier industry including structural factors and resource commitment factors that affect how well and how quickly a product is introduced to the potential adopting industry.

2.4.1 Structural factors

Just as an organization's structure can be viewed as "...a characteristic of the setting within which a manager must work" (Schermerhorn 1989, p. 178), an industry's structure is a characteristic of the setting within which a firm must work. Structural factors describe the setting of the supplier industry and include the competitiveness of the supplier industry, the reputation of the suppliers, the degree to which the technology is standardized, and the level of vertical coordination present throughout the supplier industry. Speed of diffusion of a new technology is affected by these factors (Robertson and Gatignon 1986).

Increased competition within the supply-side industry is likely to spur product improvements and reduced prices. Therefore, it would seem reasonable to expect that new technologies that are introduced and supplied by highly competitive industries are adopted quicker and by a larger portion of potential adopters than those introduced by industries that are not characterized by competitive intensity (Robertson and Gatignon 1986).

Previous technological successes by a particular supplier group appear to increase the probability that adopters will "try out" a new innovation. Robertson and Gatignon (1986) propose that the more favorable the reputation of the supplier group is, the more rapid the initial diffusion of a new technology will be.

The chance of buying a new technology that turns out to be something other than the standard can retard the initial adoption of a particular technology. Standardization could reduce the price levels associated with the new technology and speed the diffusion of the technology. Therefore, it has been suggested that the more standardized the technology is, the more rapid the adoption and diffusion of that technology should be (Robertson and Gatignon 1986).

Industries in which suppliers and customers have a high degree of vertical dependence tend to form interlocking relationships and high levels of coordination (Gatignon and Robertson 1989). Firms that are linked to suppliers may serve as beta test sites for new technology and receive preferential advance information as well as quicker delivery dates. This increased flow of information could increase the likelihood of adoption. Gatignon and Robertson (1989) found empirical evidence regarding the use of laptop computers to support the claim that greater vertical coordination between suppliers and customers enhances the probability of adoption.

2.4.2 Resource commitments

Robertson and Gatignon (1986) claim that "[t]he allocation of resources which a supplier industry makes to a new technology will have a major bearing on the speed of diffusion. Both resource commitments to (1) ongoing R&D and (2) marketing programs will positively affect diffusion potential" (p. 5).

Studies regarding motives for technology adoption claim that product improvements through enhanced technologies ultimately result in faster and broader adoption of technologies (e.g., Skinner 1984, Robertson and Gatignon 1986, King and Ramamurthy 1992, Knudsen et al. 1994, MacPherson 1994). It would make sense that increased research and development (R&D) allocations should also be associated with increased levels of adoption. Robertson and Gatignon (1986) propose that greater expenditures in R&D by supplier firms within an industry should lead to enhanced technologies that are more likely to address the customers' needs. This improved response to the customer should lead to a more rapid diffusion process for new technologies and higher levels of adoption.

Marketing strategies affect the diffusion of an innovation throughout a particular industry. Incentives offered to firms by suppliers of the new technology are most often price related and they encourage adoption (Gatignon and Robertson 1989). Adequate funds in marketing research are necessary to acquire customer input to help guide R&D in product development and enhancement (Robertson and Gatignon 1986). This cooperation between potential adopters and developers suggests that marketing resources could be complementary to the vertical coordination factor discussed earlier.

2.5 Characteristics of the adopter industry

The industry within which a potential adopting firm operates affects receptivity to innovation. In some industries there may be competitive pressure to consider new technologies and in others there may be a general lethargy (Robertson and Gatignon 1986). "The diffusion pattern at the industry level is the outcome of the distribution of individual firm adoption decisions. These individual firm adoption decisions are influenced by the compatibility between the innovation's characteristics and those of the potential adopting unit"(Robertson and Gatignon 1986, p. 2-3). Adoption is further influenced and mediated by the adopter industry competitive environment.

2.5.1 Competitive intensity

Competitive intensity within an industry or within a particular market segment has been suggested as a factor in technology adoption decisions (Kimberly and Evanisko 1981, Robertson and Gatignon 1986, Gatignon and Robertson 1989, Levin et al. 1992). The effect that competition has on adoption decisions appears to be industry-specific though.

Levin et al. (1992) collected empirical evidence to support that the "greater the number of key rivals in a market, the lower anticipated profitability for the adopter and the slower the rate of intrafirm diffusion" (p. 348). They suggest that "[t]he fewer major competitors with stores of sufficient size to make the installation of scanners profitable, the higher a firm's anticipated profitability from installing scanners and gaining business" (p. 346).

Similarly, *competitive price intensity*[7] within the adopter industry was found to be negatively related to the adoption of laptop computers for use by the sales force (Gatignon and Robertson 1989). The explanation for this negative relationship centers on the assumption that technological innovations requires some financial commitment. Since high competitive price intensity within an industry usually results in reduced financial resources, the receptivity to innovation is lowered (Gatignon and Robertson 1989). As would be expected, Gatignon and Robertson (1989) found that a higher *concentration ratio of an industry*[8] is associated with increased adoption of technological innovations. The one exception appears to be the case where a monopoly exists since the firm holding the monopoly has no need to increase market share.

On the other hand, Kimberly and Evanisko (1981) found that increased competition in the form of the number of hospitals in an area increased the likelihood of adopting technological innovations. This result may stem from the conjecture that specialization and functional differentiation are responses to problems encountered in treating the wide range of acute illnesses present in patient populations. Adopting innovations in technology developed to more quickly and accurately diagnose and treat illnesses enhances

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[7]Competitive price intensity: Degree to which firms use price as a competitive tool. (Gatignon and Robertson 1981)

[8]Industry concentration: For the Gatignon and Robertson (1989) paper, the traditional market share of the three largest competitors (CR3 ratio).

the attractiveness of the hospital to patients and also to physicians. Since an increase in the number of hospitals in an area may increase the competition for *physicians* as well as patients, adopting new technologies to increase the attractiveness of the hospital would be expected.

West and Sinclair (1992) provide more evidence that the effect of competitive intensity on adoption decisions may be industry-specific. In their study of wood household furniture manufacturers, no significant differences emerged between innovators and non-innovators on perceived number of competitors for a firm's major product group. West and Sinclair (1992) did not find these results surprising since the wood household furniture industry is considered highly competitive and highly fragmented.

2.5.2 Competitors' technology

Levin et al. (1992) investigated the effect of the competing firms' adoption patterns on a particular firm's decision to adopt and diffuse optical scanners in grocery stores. They found that although rival precedence influenced the diffusion of optical scanners, differences in the time of first adoption do not play a statistically significant role in explaining different rates of diffusion throughout a firm. "To explain rates of intrafirm diffusion, the number of firms previously adopting is more important than whether the initial adoption is earlier or later" (p. 349).

In some instances, adopters care about the number of competitors adopting the same technology because there might be some "common good" element to the technology's adoption (Besley and Case 1993). For example, in agriculture, the need to build a marketing infrastructure for a new crop could spark a producer's interest in whether or not his nearby competitors are adopting the same types of technology. Also, some operators in all types of industries prefer for someone else to work the hurdles or "bugs" that often accompany early versions of a new technology (Meredith 1987). Managers may care about others' adoption decisions if they can learn from the early adopters' experiences (Besley and Case 1993).

2.5.3 Information and communication

The types of information regarding new technologies, the form the information takes and the communication channels through which the information flows impact the likelihood of technology adoption (Wozniak 1984, Robertson and Gatignon 1986, Gatignon and Robertson 1989).

Information within an industry may be shared through signals such as announced intentions and explanations for actions such as new investments, production processes, pricing systems or product introductions (Robertson and Gatignon 1986). The amount of ambiguity in those signals and the frequency with which the information is shared characterize the *communication openness*[9] of an industry. "Communication openness and information sharing are likely to increase the available information about innovations and to ease the adoption decision process" (Robertson and Gatignon 1986, p. 8). Therefore, it is not surprising that in agricultural studies, increased extension activities have been credited with speeding the time of adoption and increasing levels of adoption (e.g., Feder and Slade 1984, Wozniak 1984).

Although cosmopolitanism is usually associated as a characteristic of an individual (as described earlier), Robertson and Gatignon (1986) believe that a measure of cosmopolitanism may be applied on an industry level. They suggest that the level of international sales, the number of markets targeted, and the percentage of employees who have worked in other industries describe the cosmopolitanism of an industry. This type of integration into external information environments is expected to speed the diffusion of innovations (Robertson and Gatignon 1986).

2.6 Characteristics of the technology

Characteristics of the technology play a role in whether or not the technology is adopted (Muth and Hendee 1980). At the time of their work, Kimberly and Evanisko (1981) point out that "[l]ittle is known about how much influence, if any, variability in type of innovation will have on adoption or whether different variables may have different explanatory roles depending on the type of innovation in question" (p. 690). Perhaps more important than the actual characteristics of the technology is the perception of these characteristics by potential adopters. Rogers (1983) identified five perceived attributes of innovations: complexity, compatibility, relative advantage, observability and trialability. Farquhar and Surry (1994) summarize these characteristics and their effect on the likelihood of technology adoption:

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[9]Communication openness of an industry: "[T]he amount of potentially useful information that is communicated among competitors. Communication openness can be measured by such variables as the number of trade journals, number of trade associations, attendance at trade and association meetings, number of press briefings, informational content of annual reports, and the number of interfirm contacts which occur." (Robertson and Gatignon 1986, p. 8); "[T]he amount of potentially useful information communicated among competitors." (Gatignon and Robertson 1989, p. 37)

> "Potential adopters are more likely to adopt an innovation if they perceive that the innovation has low complexity, is compatible with their needs and wants, offers an advantage over the present system, results in observable benefits, and can be experimented with on a limited basis" (p. 21).

Ram (1987) suggests some additional perceived innovation characteristics: divisibility, communicability, reversibility, and amenability to modification. Divisibility refers to the ability of the innovation to be applied in stages. Communicability of an innovation describes the ease and effectiveness with which the results of the innovation can be disseminated to others. Reversibility refers to the ease of discontinuing the innovation if desired. "Amenability to [m]odification reflects the flexibility with which the innovation can be modified to ensure consumer satisfaction" (Ram 1987, p. 210).

Also, new technologies that are similar to others that have been failures will negatively affect the rate of diffusion (West 1990).

2.7 Expected benefits of adoption

Another segment of the literature dealing with technology adoption investigates the benefits adopters expect if they adopt certain technologies. In many instances, the adoption and implementation of new technologies is expected to yield some competitive advantage, especially if the adopting firm is among the first in the industry to adopt (Besley and Case 1993, Stenbacka and Tombak 1994).

2.7.1 Cost reductions

Several authors suggest that one of the primary reasons firms adopt certain technologies is that they expect costs to go down as a result of implementing the technology (e.g., Robertson and Gatignon 1986, Meredith 1987, Wiarda 1987, Lefebvre et al. 1991, Griffith et al. 1995). These costs may be in production, distribution, or marketing (Robertson and Gatignon 1986) including the area of labor savings (Meredith 1987, Wiarda 1987, Rosenberg et al. 1990, Harvey et al. 1992, King and Ramamurthy 1992).

Productivity and performance efficiency (including material cost savings) are potential benefits that firms expect to achieve when considering a technology adoption decision (Wiarda 1987, West and Sinclair 1991, Harvey et al. 1992, King and Ramamurthy 1992). In their empirical study of 222 American Midwest machinery manufacturers, King and Ramamurthy (1992) found that "[a]lmost all of the firms (96%) stated that their primary objective in considering [advanced manufacturing technologies] was to enhance efficiency of internal operations and profitability" (p. 132).

In MacPherson's (1994) study of 146 small and medium-sized manufacturing firms in western New York, firms were designated as either import-competing or export-competing. The import-competing group (furniture, textiles, metal fabrication) adopted flexible manufacturing systems or parts of flexible manufacturing systems with the primary objective of cost reduction. MacPherson suggests that "the cost-minimizing approach is likely to be more common among [small and medium-sized manufacturing firms] that serve mature markets where product standardization is fairly widespread" (p. 148). Also, the expectation of cost savings appears to play a bigger role in the adoption decision for small companies that have not previously adopted many innovations than it is for small firms that have more experience with newer technologies (Lefebvre et al. 1991). Reductions in setup/changeover times also have been cited as reasons for technology adoption (Skinner 1984, Meredith 1987, Knudsen et al. 1994, MacPherson 1994). Skinner (1984) notes that competitively unique technologies "can shift economies of scale so that short production runs are feasible, and create new production economies, allowing for a richer product mix, more product proliferation, and more customer specials" (p. 117). The telecommunications industry implemented certain technologies to reduce the time an operator spends on a directory assistance call. The expectation was that a one-second decrease in the average time per directory assistance call results in $1.7 million in labor savings (Lynch and Osterman 1989).

Some new technologies are expected to effect reductions in inventories thus leading to lower inventory carrying costs in production and in distribution by reducing the depth of inventory quantities (Skinner 1984). However, the increase in product mix and product proliferation may result in more complex inventories to manage since the breadth of products may increase (Skinner 1984). Also, new manufacturing technologies may be expected to lead to improved management and economy of space by freeing up floor space (Meredith 1987, King and Ramamurthy 1992).

2.7.2 Higher quality

Another motivating factor for adopting new technologies is the push to provide higher quality items to customers (Skinner 1984, Robertson and Gatignon 1986, Wiarda 1987, West and Sinclair 1991, King and Ramamurthy 1992, Knudsen et al. 1994, MacPherson 1994). Consistent, high quality and high reliability are important not only in getting and retaining customers, but they also reduce the costs associated with rework, scrap, and technical assistance to customers. Knudsen et al. (1994) found that quality was more often cited as the single motivating factor or expected benefit at multi-plant operations than at independent single-plant operations. MacPherson (1994) notes that the quality of the product being produced is not the only quality issue considered in the adoption of some types of technology. He cites examples where firms adopt flexible manufacturing techniques "...in order to compensate for variable input quality (including late input delivery)" (p. 148) in addition to improving the quality of the output product.

2.7.3 Increased customer service and flexibility

Some firms expect to be able to provide new benefits for the firm's customers if a new technology is adopted (Robertson and Gatignon 1986). Shortened delivery cycles are one type of improved customer service that many technologies are expected to stimulate (Skinner 1984). Flexibility to respond quickly to market-related changes or customers' needs was found to be a motivating factor in adoption of advanced manufacturing technologies (Wiarda 1987, King and Ramamurthy 1992). Increased flexibility allows firms to "produce both more products and more models of existing products" (Knudsen et al. 1994). The importance of smaller batch sizes and the subsequent ability to handle a wider family of parts is underscored by King and Ramamurthy (1992). MacPherson (1994) found that production flexibility was a key motivating factor for the adoption of flexible manufacturing technologies especially for those firms looking to expand their sales in foreign markets (manufacturers of scientific instruments, industrial machinery, and electrical products).

2.7.4 New markets

Adoption of new technologies can also lead the way into new market segments for some firms (Robertson and Gatignon 1986, MacPherson 1994). Flexibility to respond quickly to market-related changes is one reason given for adopting advanced manufacturing technologies (King and Ramamurthy

1992). MacPherson (1994) suggests that "firms that manufacture small batches of specialized products often adopt [flexible manufacturing system] techniques with a view to achieving better market responsiveness (serving highly differentiated demand within a specialized product market). For firms in this category, a key requirement is the ability to respond quickly to highly specialized market needs--and deliver excellent products at the same time" (p. 148). However, the designation of growth as a cause or as an effect is debatable. Oakey and O'Farrell (1992) point out that "[w]hile the adoption of CNC machines might have prompted growth, rapid expansion might also have been the trigger for CNC adoption" (p. 168).

2.7.5 New products

One way that firms compete (especially small firms) is through new products (Meredith 1987). Some firms expect the implementation of new technologies (such as CAD/CAM) to reduce the new product development cycle and to make possible entirely new products (Skinner 1984). The promise of producing relatively specialized products in small lot sizes on demand is one potential benefit that was considered in the decision to adopt group technology approaches to manufacturing (Knudsen et al. 1994).

2.7.6 Reputation as technology leader

The sophistication of the company's image is becoming more important in today's global marketplace. Becoming a technology leader or at least being recognized as technologically aware proved to be a significant source of justification for advanced manufacturing technology adoption in over 80% of the manufacturing firms surveyed by King and Ramamurthy (1992). Likewise, Meredith (1987) found evidence that an improved image of the firm in the eyes of its customers, competitors, and employees is one of the benefits that managers of small firms associate with the adoption of new manufacturing technologies. Also, an earlier discussion pointed out that adopting new technologies is one strategy for hospitals to recruit and retain physicians as well as patients (Kimberly and Evanisko 1981). This could be interpreted as a response to the hospital's reputation as a technology leader. The image of the company as a progressive technology leader appears to be more important as the number of new technologies already adopted increased (Lefebvre et al. 1991).

2.7.7 Production capacity

Increasing production capacity is another benefit manufacturers expect to gain through technology adoption (Meredith 1987, West and Sinclair 1991, Harvey et al. 1992). Since new technology is sometimes adopted with the expectation of reduced cycle times and lower work-in-process levels, many adopters also expect an increase in production capacity (Meredith 1987). Harvey et al. (1992) argue that increasing production capacity is a particularly often cited expected benefit for small firms. "Small companies are very cost conscious and they need an immediate and tangible motive to invest in technology. A company which is operating at or near its peak capacity will often consider the acquisition of [new manufacturing technologies] as a means to increase its capacity" (p. 355). Increased production capacity is often expected when adopting a new technology to replace old or outdated equipment. Replacing older equipment was found to be a driving force in technology adoption decisions in the wood household furniture industry (West and Sinclair 1991).

2.7.8 Safety and environmental concerns

Improved safety within the manufacturing environment may be another force behind the adoption of some new manufacturing technologies in small firms (Meredith 1987). However, it might be more of a side issue than a driving force. Adopting manufacturers from six mid-western states were asked to rate the importance of safety or environmental concerns as a reason for adopting programmable technologies (Wiarda 1987). Their responses were recorded on a scale of 1 to 5 with 1 representing "Not at all important" and a 5 representing "Extremely important." Despite 15% of the respondents giving safety/environmental concerns a 4 or a 5, the average score was a 2, indicating that most of the other 85% of the respondents felt that safety or environmental concerns had little or no impact on their decisions to adopt programmable technologies.

2.8 Serendipity

One final point regarding factors that drive the technology adoption decision process is the effect of serendipity. Langley and Truax (1994) point out that Mohr (1987) "...suggests that innovation is easiest when standard operating procedures or 'organizational routines' tend to drive organizations to consider new technology in the natural course of events (i.e., through a serendipitous process)" (p. 621). The organizational routines that Mohr refers to may include hiring individuals who happen to be knowledgeable about the technology (relates to technical expertise), using new technology to use up slack resources (might relate to cost reductions), or imitation of other firms (relates to competitors' technology). The key point here is that while these routines might characterize the organization or their motives in technology adoption, the manner in which they are viewed comprises a non-deterministic attitude towards the innovation process.

2.9 Inhibitors to adoption

A small segment of the literature discusses inhibitors to adoption. Most of the studies in this area are industry specific and many of the inhibiting factors appear to be technology specific.

2.9.1 Capital investment

The up-front investment associated with many new technologies inhibits adoption of many new, high cost technologies (Skinner 1984, King and Ramamurthy 1992). Whether this inhibition results in a total rejection of the technology or merely delays the adoption of the technology until it has been proven to be effective in other firms in the same industry, it affects the technology's attractiveness. The negative effect of the capital investment is compounded by the interest rate or cost of capital (Tsur et al. 1990). However, Skinner (1984) points out that some technologies can actually "minimize investment in plant and equipment" (p. 117) if a more long-term perspective is applied to the adoption decision. He goes on to suggest that investments in operations technology have been discouraged since capital budgeting is based primarily on return on investment, rather than on strategic analysis.

The issue of large capital expenditures is particularly pertinent when discussing adoption behavior of small firms (Meredith 1987, Harvey et al. 1992, Oakey and O'Farrell 1992, MacPherson 1994). "While a number of questions confront the small firm owner considering investment in new equipment (for example, the fluctuating level of customer demand), a key variable in the 'investment equation' will be the price of capital that may need to be borrowed to fund new investment" (Oakey and O'Farrell 1992, p. 167). Likewise, MacPherson (1994) found that although many companies consider the adoption of flexible manufacturing systems, the technology adopted may be a specific part of a full system. "Fully integrated systems are rarely evident at the [small or medium-sized manufacturing firms] level, if only because most small manufacturers lack the investment capital required for system-wide retooling" (MacPherson 1994, p. 147).

For small firms, the acquisition of a new, high-priced technology may trigger the failure of the company unless the prospects of high quality and improved processing efficiency that the technology offers are converted into cash fairly quickly (Harvey et al. 1992). This supports the earlier suggestion that firm size is positively related to adoption.

2.9.2 Management

Skinner (1984) suggests that one roadblock to technology adoption is "top management's perception of operations as a kind of 'productivity machine' rather than as a potential strategic resource" (p. 121). "The inexperience of top managers in manufacturing makes them unreceptive to major innovation in factory technology." (p. 122). Part of this attitude could be that the performance reward systems in many organizations are based on short-term performance (Achenbach 1987, Dimnik and Johnston 1993). "People do those things they perceive to be in their own best interest" (Achenbach 1987, p. 806). If performance rewards are based on short-term returns on capital investments, then it is not likely that a manager would enthusiastically support a capital-intensive proposal whose returns, while substantial, may take a while to realize.

Meredith (1987) cites organizational inertia as a potential source of hindrance to technology adoption. He goes on to mention that constantly mobile managers, fast-track executives, and "merry-go-round" job rotation programs evoke little commitment to new technologies. "Shop workers with 15 and 20 years seniority ... commonly see a new manager every 2 or 3 years, each with his or her own favorite new 'project' to help the company, so there is little incentive for them to make another (temporary) change" (p. 256).

2.9.3 Difficulty in integrating with current systems

King and Ramamurthy (1992) found that difficulty in integrating the disparate pieces of advanced manufacturing technology automation with the current system inhibits their adoption. "Radical new equipment often does not mesh with existing equipment." (Skinner 1984, p. 122). The difficulty of integrating CNC equipment with other machinery on the shopfloor was seen as an inhibitor in the technology adoption process for small mechanical engineering firms in Great Britain (Oakey and O'Farrell 1992).

2.9.4 Training machinery operators

In some instances, the need to retrain machinery operators to use the new technology was considered a deterrent to adopting technology (e.g., Oakey and O'Farrell 1992). In Japan, a network of research institutes and technology centers are maintained for the purpose of aiding and training workers and firms in new products and processes. This enables them to keep up with state-of-the-art technology. Similar networks exist in the Italian woodworking industry (Sommers and Leinbach 1989).

2.9.5 Regulatory compliance

Sometimes, the use of a new technological process requires certain permits or other regulatory compliance. This is especially true when dealing with technologies that may adversely affect the environment. The lengthy process of applying for and obtaining permission to install the new technology has been cited as one barrier to technology adoption (Moore 1994).

2.10 Post-adoption effectiveness

In the literature, a few studies have explored the question of "so, did you get what you thought you were going to get?" with respect to new technologies. In almost every case, there were unexpected problems with implementation and effectiveness of the technology. In addition, not all expected benefits were realized while some benefits that were not expected *did* occur.

For example, one of the anticipated benefits associated with new technology adoption is reduced labor costs. In their study of a segment of the telecommunications industry, Lynch and Osterman (1989) showed "...how the introduction of new technologies reduced the demand for labor in some occupations while it increased the demand in others" (p. 205). Then again, Oakey and O'Farrell (1992) found that the adoption of CNC technology generally resulted in reduced delivery times and reduced setup times, both of which have been cited in the literature as expected benefits of technology adoption.

A variety of factors have been suggested to explain why the benefits expected from a new technology failed to materialize. One of the most basic reasons for disappointment in the effectiveness of the implementation of a particular technology is that technology characteristics may differ from those expected (Madan Mohan 1993). Either the technology does not perform to the specifications given or some aspect of the technology produces a negative side-effect to the overall productivity of the operation (e.g., unacceptable noise level). Meredith (1987) indicates that previous research by Jaikumar (1984) shows that "the large firms are finding it difficult to take advantage of [the increased flexibility made possible by the new technology], preferring to maximize the utility of the complex, expensive equipment, once the bugs have been laboriously worked out, rather than further experimenting with it to see what it can do" (p. 255).

Labor quality was cited as a very important factor in flexible manufacturing system implementation (MacPherson 1994), group technology application (Knudsen et al. 1994), and implementation of programmable technologies (Wiarda 1987). The residual work habits of labor and management and negative attitudes of workers and middle managers toward productivity improvements were cited as hurdles to successful implementation of new technologies (Harvey et al. 1992, Knudsen et al. 1994).

Despite the argument that newer firms would not be inhibited by "accumulated ageing management practices and/or machinery" (p. 170), Oakey and O'Farrell (1992) found that problems with the post-adoption integration of CNC equipment proved greater and more often by newer firms. They suggest that "[i]t may be the case that a generally less stable financial environment in newer firms, together with a poorer understanding of the nature and amount of CNC capacity required, renders the adoption of such machines likely to carry a higher risk of introductory problems" (p. 170). In interviews with 34 CEOs of small or medium-sized firms, MacPherson (1994) discovered that "[c]ontrary to popular opinion, many of these CEOs indicated that older production workers (especially engineers and technicians) are among the most adaptable when it comes to operating, calibrating and troubleshooting new equipment" (p. 159).

In some instances, many of the factors that affect adoption were found to be correlated with post-adoption success as well. For example, in their study of British mechanical engineering firms, Oakey and O'Farrell (1992) found that "...it is the small firm with a limited commitment to CNC that experiences the most difficulties in terms of maximizing post-CNC adoption benefits to the firm" (p. 174). They also found that the number of times a type of technology was purchased was positively correlated with successful implementation. They present a 'critical mass of experience' argument where the introductory problems associated with a particular technology are more fully anticipated and more readily addressed as the number of times the technology is acquired increases.

Baker's (1992) study showed that manager and firm characteristics which influence adoption do not necessarily affect successful use of computer systems and vice versa. He found that the age and education of the manager, the size and type of the firm, the manager's involvement in the purchase decision, the presence of a computer specialist and the number of years of computer use all had some effect on the successful implementation of computers once they were adopted regardless of whether or not each factor held a significant influence on the adoption decision.

Management practices affect the success implementation of a new technology as well as its initial adoption. Knudsen et al. (1994) suggest that a lack of adjustments in labor or management practices when adopting a new technology constrains the effectiveness of the technology. The reluctance of management to delegate certain decisions to shop floor workers (assuming that the new technology is the impetus for the change in authority) can negatively impact the effectiveness of the innovation (Knudsen et al. 1994). On the other hand, both Meredith (1987) and Baker (1992) found that participation in the implementation process by top management (who are more likely to remain in their jobs for longer periods of time) appeared to have a significant, positive impact on the success of the new technology.

Also, the ability to integrate a new technology into the current production line is not always adequately considered. For example, MacPherson's (1994) study revealed that bottlenecks resulted when flexible manufacturing cells were placed into a production line without consideration of the difference in the speed at which the cell could produce its output and the speed at which the next subsequent machine could process that output. In the educational arena, support for the user to acquire the necessary skills proved to be a key element to successful implementation of new educational tools (Farquhar and Surry 1994).

2.11 Furniture and wood products specific studies

In 1987, Wiarda reported results of a study of adoption of programmable automation in a six-state region including Michigan, Ohio, Indiana, Illinois, Wisconsin, and Minnesota. Although the study involved firms classified under ten different major industries or Standard Industrial Classification (SIC) groups, results pertaining to companies classified under lumber and wood products (SIC 24) and furniture and fixtures (SIC 25) are briefly discussed. Of the establishments studied[10], firms in these two industries were the least likely technology users. At the time of the study, none of the technologies that proved to be common among the entire sample were adopted by even 5% of the lumber and wood products establishments, implying a low degree of programmable technology use in the industry. Within the furniture and fixtures firms, any combination of two or more programmable technologies was unusual. Wiarda points out that these industries historically have competed on the basis of price rather than product design, quality, or technical content.

MacPherson's (1994) study involved a small sub-sample of western New York's furniture manufacturers. While the number of manufacturers in this sub-sample is very small (18) and the results could not be generalizable to the entire furniture manufacturing industry, it is interesting to note the findings. In this study, MacPherson found that the top two motivating factors (of those supplied on a mailed questionnaire) for adopting flexible manufacturing techniques were to compete with imports and to reduce unit costs. These two factors received nearly identical average scores from a 5 point Likert-type scale. The other motivating factors or expected benefits in decreasing order of importance were: product improvement, customization of output, faster turnaround new product introduction and finally, expansion into export markets.

The MacPherson study ranked the benefits that the manufacturer attributed to the adoption of flexible manufacturing techniques. The furniture manufacturers ranked lower unit costs, improved quality, and reduced materials wastage as their top three benefits. Other benefits in decreasing order of importance

[10]Other industries represented in the sample include: stone, clay and glass products; primary metal industries; fabricated metal products; non-electrical machinery; electrical and electronic machinery; transportation equipment; measuring, analyzing, and controlling instruments; miscellaneous manufacturing industries.

were: reduced labor costs, higher machine utilization, lower defect rates, ease of batch production, faster new product development, reduced work-in-process, ability to customize, greater market responsiveness, faster turnaround, reduced inventory, reduced lead times, and easier product design (MacPherson 1994).

Greber (1993) looked at the Pacific Northwest timber industries with an eye toward technological change. He suggests that the expected benefit or motivation of labor cost reductions will not have the impact on technological change that it had in the past. "With the changing availability of timber and the likely limited access to capital by producers in the region, the focus of technology is apt to be on raw material saving and capital saving technological change" (p. 36).

Rosenberg et al. (1990) state that "[p]rospects for technological change in forest products are heavily shaped by 1) commitment of resource to research and development (R&D) within the private and public institutions that comprise the forest products industry and its suppliers; and 2) developments in industries that are remote from forest products" (p. 15). "Technological innovations in the forest products industry tend to have a strong labor-saving bias" (Rosenberg et al. 1990, p. 16). However the reason for many innovations has been raw material shortages. These innovations facilitate the use of smaller diameter logs and "inferior timber sources" (p. 17). Seemingly superior technologies may not be widely adopted in the forest products industry because they do not decisively reduce costs. This is consistent with Harvey et al.'s (1992) claim that small firms need quick, tangible motives for technology adoption since the forest products industry is characterized by a large number of small firms.

As is the case in other industry studies, the adoption and diffusion of new technologies in the forest products sector is somewhat contingent on the economic impact of complementary inputs. "New technologies always represent clusters of characteristics, so the industry must cope with the more fundamental matter of optimizing those characteristics, suppressing some and enhancing others, while minimizing risk and uncertainty" (Rosenberg et al. 1990, p. 18). The heterogeneity of the raw material slows down the development or application of new technologies. "The behavior of wood is highly variable from one species to another and also from one location in the log to another....Technological problems are often too subtle and multivariate for scientific methodology to offer generalized results" (Rosenberg et al. 1990, p. 20). "A major thrust of technological change in the forest products industry has been to overcome, or at least reduce, the effects of heterogeneity. Many innovations have involved taking a diversity of low quality timber resources and converting them into products with lumber-type or plywood-type characteristics" (Rosenberg et al. 1990, p. 20-21).

"In summary, major reasons for the slow adoption of some important new technologies in forest products are 1) the body of technologically relevant information is highly fragmented; 2) the stock of information relevant to any given use is expanded very slowly; 3) the feedback loops from use and experience are much less significant as diffusers of useful information than is the case in other industries; and 4) over a wide range of productive uses, scientific theory, although valuable, cannot play a very effective role in providing information tailored to the particularities of local use conditions." (Rosenberg et al. 1990, p. 21). Rosenberg et al. (1990) recommend the following actions for enhancing technological change: 1) monitor and evaluate developments in other industries; 2) monitor developments in other countries; 3) focus on internal dynamics of technological change; and 4) study the economics of adoption and diffusion of new technologies in the forest products industry.

West and Sinclair (1991, 1992) reported survey results of 222 wood household furniture manufacturers. The number of production employees in the firms surveyed ranged from less than twenty to over a thousand with 43% of the respondents falling in the 0-19 production employees categories. Only 17 respondents (8%) were located in the South central region of the United States[11]. Products manufactured by the respondents included factory-assembled, ready-to-assemble (RTA), and knock-down (KD) wood household furniture[12]. In this study, respondents were asked to indicate adoption actions and plans with respect to 24 process technologies. The sample was divided into innovators and non-innovators by the following criterion: firms adopting seven or more of the twenty-four technologies were considered innovators and all others were considered non-innovators.

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[11]In this survey, the South central region of the United States was comprised of Texas, Louisiana, Arkansas and Oklahoma

[12]RTA furniture was defined as assembled by the final consumer and KD furniture was defined as assembled prior to sale by a distributor or retailer.

Larger firms adopted more of these manufacturing technologies than smaller firms. "Although they [large firms] planned to invest more money in capital equipment in total over a 12-mo and 5-yr period, they did not plan to spend more per production employee than smaller firms" (West and Sinclair 1992). Further investigation revealed that most of these large firms were members of larger corporations where the risks of capital expenditure are diversified. Survey results also showed that the more innovative firms in the sample produced a slightly higher priced line of furniture than less innovative firms.

With respect to communication behavior, the only significant difference between firms classified as innovators and those classified as non-innovators was in their dependence on trade and equipment shows for information (West and Sinclair 1992). The innovator group indicated that these shows are a more important source of information than did the non-innovator group.

Characteristics of the primary decision-maker appeared to be closely associated with adoption behavior. Cosmopolitanism (measured as international travel) was positively associated with technology adoption, as were professionalism (measured as the number of furniture markets, trade shows, and association meetings attended each year) and opinion leadership (measured as the relative frequency that other firms contacted them for information concerning a new technology).

The West and Sinclair study also found that innovators within the sample employed more manufacturing engineers and product design engineers than did non-innovators. In addition, firms in the innovator category expressed a greater degree of technical progressiveness (measured by degree of agreement with the statement "Our manufacturing organization tries to be the first in our industry to implement new production technologies and methods") than did firms in the non-innovator category (West and Sinclair 1992).

2.12 Math models

The key question in technology adoption model development is "how do we measure technology adoption?" Several measures have been developed in technology adoption literature. Many studies have focused on the yes/no decision to change as the dependent variable (e.g., Feder and Slade 1984, Wozniak 1984, Gatignon and Robertson 1989, Harper et al. 1990, Hodges and Cubbage 1990, Baker 1992). Wiarda (1987) and Griffeth et al. (1995) discuss adoption rates. In an ex-ante analysis, Griffeth et al. (1995)

suggest expressing livestock technology adoption rates in terms of either the number of producers expected to utilize the technology or the number of animals affected by the technology. In addition to discussing adoption rates as the percentage of potential adopters who have implemented a new technology, Wiarda (1987) constructed a breadth score describing the number of new technologies a firm has adopted and a depth score describing how intensively a firm is using whatever technologies it has. Levin et al. (1992) focus on the speed of intrafirm diffusion. Time series studies have often used the fraction of adopters in the region at a particular point in time as a measure of technology adoption (Besley and Case 1993).

2.12.1 Logit and cross-sectional models

The logit model is one of the most commonly used binary choice models used in areas such as agricultural and forest economics (Hodges and Cubbage 1990). The binary decision in this case is a yes/no decision regarding whether or not a particular technology should be adopted. This model is typically based on cross-sectional data that represents a single point in time.

The logit model is associated with the cumulative logistic probability distribution of adoption. The logistic probability model can be used to transform a binary dependent variable such that predicted outcomes will be within the (0,1) interval for all values of the independent variables. The result will be a monotonically increasing function of the probability of adoption (Hodges and Cubbage 1990, Wozniak 1984).

The logit model is given by :

$$P_i = \frac{1}{1 + e^{-(\alpha + x_i\beta)}}$$

where P_i = probability of the ith individual adopting a certain innovation

e = base of natural logarithms

α = intercept term

β = vector of coefficients

x_i = vector of independent variables associated with the ith individual

(Wozniak 1984, Baker 1992, Johnson and Wichern 1992 (p. 553)).

Cross-sectional data studies can be described as belonging to one of two groups: snapshot models and recall models. Snapshot models consider technology use by an operator, firm, industry or set of industries at a single point in time. For example, Wiarda's (1987) study relies on cross-sectional data which reflects a single slice in time of a large sample of companies from a variety of industries. Many snapshot models attempt to quantify the probability of adoption of a new technology by applying a standard normal distribution function to the gain achieved through use of the new technology. Typically, the gain to an operator i is given as $\gamma x_i + u_i$ where x_i are operator and operation characteristics and u_i is an independently and identically distributed operation specific *ex ante* shock (assumed to be normally distributed). The snapshot model becomes:

$$Prob(adoption\ by\ farmer\ i) = \phi(\gamma x_i / \sigma_u)$$

where $\phi(\cdot)$ is the distribution of the standard normal.

The emphasis of these models is on the impact of the operator/operation characteristics x_i on decisions to adopt new technology and not on the adoption process itself or how the adoption and implementation processes proceed. For example, Wozniak (1993) used a log-linear probability model to estimate the joint occurrence or nonoccurrence of information acquisition and innovation adoption and whether adoption takes place early in the innovation's life cycle or later, after the technology is considered mature. Three dichotomous dependent variables were identified:

$$N_i = \begin{cases} 1 \text{ if innovation } i \text{ is adopted, } i = 1,2 \\ 0 \text{ otherwise} \end{cases}$$

$$I_j^T = \begin{cases} 1 \text{ if manager talked with information provider } j \text{ about the innovation,} \\ \quad j = \text{P,E} \\ 0 \text{ otherwise} \end{cases}$$

$$I_j^A = \begin{cases} 1 \text{ if manager attended demonstrations or meetings sponsored by} \\ \quad \text{information provider } j \text{ on innovation, } j = \text{P,E} \\ 0 \text{ otherwise} \end{cases}$$

where $i = 1$ for the mature technology or $i = 2$ for the current innovation and $j = \text{P}$ for a private information source or j = E for a public information source. Other variables included the number of years of schooling completed by manager, the number of days of work loss due to health, the number of cattle sold for slaughter, debt on machinery and livestock, off-farm wage income and other non-farm income (e.g., stocks, bonds, mutual funds, savings accounts). All of these variables deal directly with characteristics of the operator or of the operations.

Recall models are based on surveys that ask operators to recall circumstances surrounding the adoption of a certain technology. These types of models allow the inclusion of a history of earlier awareness of or use of the technology. These models also incorporate a set of interaction terms that allow the influence of operator/operations characteristics to change over time. It is important to understand that these interaction terms do not represent the changes in operator and operation characteristics that occur over the diffusion period; these characteristics are assumed to remain unchanged over time.

2.12.2 Sequential decision models

Sequential decision models are based on the notion that technology adoption is a sequential decision process that can be decomposed into a certain number of phases with each phase being made up of different types of activities (Langley and Truax 1994). Levin et al. (1992) developed a two stage math model investigating the adoption and diffusion of optical scanners in grocery stores in the late 1970's and early 1980's. They predicted the speed of intrafirm diffusion of optical scanners in grocery stores in Stage I and then determined the characteristics of the market environments (adopter industry) that explained differences in these estimated diffusion rates in Stage II.

The Stage I model built on Mahajan and Peterson's (1985) "fundamental diffusion model" to become:

$$\frac{dN(t)}{dt} = bN(t)[k_1 + k_2S(t) - N(t)]$$

where $dn.(t)/dt$ is the rate of diffusion at time t, $N(t)$ is the cumulative number of adopters up to time t, b is a measure of speed of diffusion, $S(t)$ is the number of operations in a market owned by a firm at time t and $k_1 + k_2S(t)$ represents the number of potential adopters at time t.

Breaking this model down into its discrete analog results in:

$$N(t + 1) - N(t) = bk_1N(t) + bk_2N(t)S(t) - bN(t)^2$$

As shown in Figure 2.2, the fundamental diffusion model builds a sigmoid-shaped curve. The steepness of the sigmoid is determined by b. The modified version of this model allows for the number of potential adopters to vary over time, but it still retains its sigmoid shape to a large extent. However, if a drop occurs in the number of operations towards the end of the time horizon, the cumulative number of adopters at time t can be greater than the number of potential adopters at time t and the cumulative number of adopters can actually decrease (see Figure 2.3).

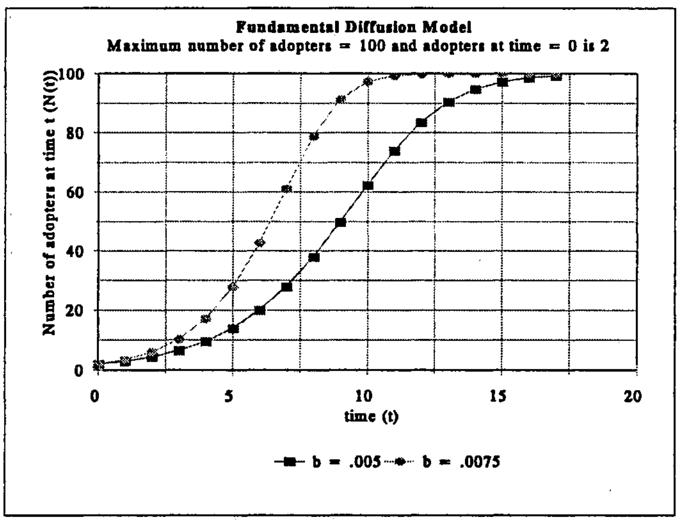

Figure 2.2. Fundamental diffusion model as reported in Levin et al. (1992)

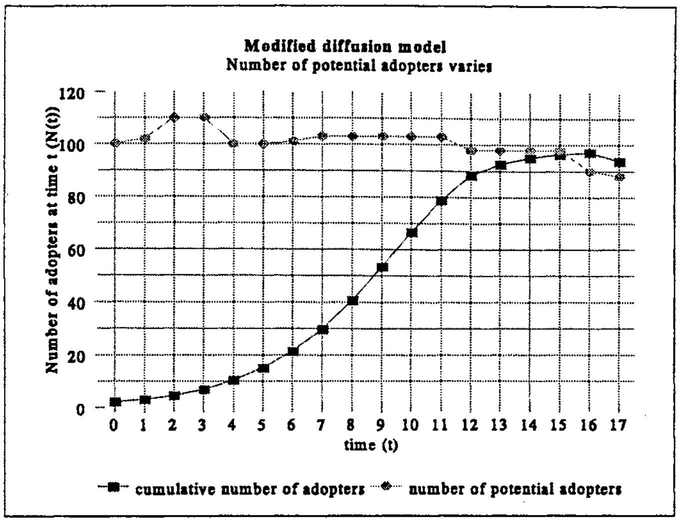

Figure 2.3. Modified diffusion model as proposed by Levin et al. (1992)

Saha et al. (1994) developed a three phase model where Phase I represented information collection; Phase II represented the decision on whether or not to adopt the technology; and Phase III represented the decision on how much to adopt. Phase I utilized a vector **d** containing the producer's relevant economic and demographic characteristics; if the information level the operator has achieved through these characteristics, $I(\mathbf{d})$, is greater than some threshold level i^0 of information, then he/she has heard about the new technology. The remaining phases are conditional upon the information level of the operator ($I(\mathbf{d}) > i^0$).

The second phase maximizes expected utility of wealth. Since this model was developed in relation to increasing milk production on dairy farms, it is likely that initial adoption will not necessarily affect the entire herd. Thus, the expected utility function relies on the number of cows in the traditional production process (m) and the number of cows affected by the new technology (z); m and z comprise total herd size ($m + z = x$). In this formulation "the optimal number of cows in the traditional production process is determined solely by output and input prices and is unaffected by risk considerations" (Saha et al. 1994, p. 838).

Phase III deals with choosing the optimal number of applications of the new technology. As stated before, this type of production allows adoption on a partial basis; just because the technology is adopted, it is not necessarily applied to all production units (in this case dairy cows). The adoption intensity is a function of sociodemographic characteristics as well as subjectively formed moments of the uncertain yield distribution.

2.12.3 Time series models

Besley and Case (1993) reviewed several empirical approaches to the analysis of technology adoption. The first type of model employs time-series studies that tend to model the pattern of adoption as a logistic-shaped function over time. The standard form of this type of study has been:

$$p_{it} = f(p_{it-1}) + \varepsilon_{it}$$

where p_{it} = the fraction of adopters in region i at time t and $f(\cdot)$ is a function of characteristics of the industry or, more often, of the region. One problem with this type of analysis is that the main purpose is to identify the characteristics of the region that are associated with technology adoption and not to identify characteristics that are associated with non-adoption nor characteristics regarding the decision-making process.

2.12.4 Markov processes

Besley and Case (1993) suggest using a Markov process approach to modeling the process driving technology adoption. Writing the probability of observing any value of the state variable in the future as a first-order Markov process allows maximization of an operator's value function using a recursive process. The state variables might represent any of the following: assets that are available to pay for implementation of the new technology, the body of knowledge about the new technology (grows over time), or a dichotomous variable indicating whether or not the investment was ever undertaken previously.

Even though Wiarda (1987) does not present a formal Markov process, she does provide an empirically-based model of adoption behavior with respect to thirteen different programmable technologies. The graphical model shows which technologies a firm is likely to adopt if it only adopts one technology, and how that initial choice typically branches out into choices of technology pairs and triples.

2.12.5 Innovativeness scores

Some studies have focused on innovativeness as "the degree to which an individual is relatively earlier in adopting an innovation than other members of his system" (Rogers 1983, p. 22). Langley and Truax (1994) cite several instances where the appropriate unit of analysis when investigating the technology adoption process is the individual technology decision. Studies using a single innovation as a measure of innovativeness have been criticized because "...the adoption of a single innovation may be idiosyncratic and, therefore, not a representative measure of innovativeness in general" (West and Sinclair 1992, p. 512-513).

An alternative approach is to determine how many of a prespecified list of new processes or technologies a firm has adopted at a given point in time. Again, this is a snapshot of the industry. However, it has been argued that firms whose average adoption time is shorter tend to own more new products or processes (West and Sinclair 1992). Therefore, an innovativeness score based on the number of new technologies adopted at any point in time may give some insight into adoption behavior, and may be expressed as:

$$II = \sum_{i=1}^{n} w_i s_i$$

where II = the firm's innovativeness score

n = the number of selected (significant) items

w_i = the weight attached to the ith item, and

s_i = the individual score on the ith item (Midgley and Dowling 1978).

A similar type of score, called an adoption quotient, has been applied in the agriculture literature (Anantharaman et al. 1993). Anantharaman et al. (1993) modified the adoption quotient formula developed by Chattopadhyay in 1963. The modified formula is:

$$AQ = \frac{\sum_{i=1}^{n} (e_i w_i / P_i) \times 100}{\sum_{i=1}^{n} w_i}$$

where e_i = extent of correct adoption of the ith practice

P_i = potential area for adoption of the ith practice

w_i = weighting given to the ith practice

n = number of improved practices under consideration.

If $s_i = 100e_i / (p_i(\sum w_i)$ for all i ($i = 1, ..., n$), then the two measures (innovativeness score and adoption quotient) are the same.

2.12.6 Breadth and depth scores

Wiarda's (1987) measurements were also based on the number of new technologies adopted at a single point in time (breadth of adoption), but she took this one step further. She devised a depth score to recognize the difference between the use of 25 CNC machine tools in a 75-man shop and the use of a single CNC machine tool in a 75-man shop. This measurement indicated the intensity of use of whatever technologies a firm has.

The breadth score for a firm was simply the number of technologies the firm had adopted out of the thirteen programmable technologies considered in the study. Comparing mean breadth scores for each industry gives some indication of the degree to which programmable technologies have penetrated various industry sectors.

To calculate a depth score, the number of machines or workstations a firm had per 100 employees was figured for each of seven technologies. These figures (i.e., the non-zero figures) were normalized and aggregated to form a depth score.

2.12.7 Market-level impacts

"The overall approach to estimating the *ex-ante* market impacts of a livestock production technology is to calculate the economic surplus changes and distributions from its adoption" (Griffith et al. 1995, p. 180). There are two methods for calculating economic surplus (comprised of two elements: consumers' surplus and producers' surplus). In the first method, technology adoption is assumed to result in an outward shift in the product's supply curve. The method requires assumptions about the slope of supply and demand curves, the nature of the supply shift and the relationship between producer and consumer prices. The method also requires some base or initial equilibrium set of prices and quantities. These assumptions allow the effects of the shift in supply on economic surplus to be evaluated using standard formulae.

The second method involves simulating the impacts of the new technology using a quantitative market model. In this case, the relevant market variables or parameters are subjected to "what-if analyses" and the results are compared with the base model solution. Differences in prices and quantities are attributed to changes imposed by the new technology. The problem with the first model is that it is static; the problem with the second model is the development of accurate simulation models.

2.13 Theory of reasoned action

Dimnik and Johnston (1993) use the theory of reasoned action (TORA) to explain the championing behaviors of manufacturing managers. TORA is based on the assumption that people behave in a sensible manner and it explains behavior using only a few variables. Dimnik and Johnston's TORA model of championing behaviors centers around two determinants: behavioral beliefs (manager's beliefs that adoption leads to positive outcomes) and normative beliefs (manager's beliefs that other people who normally influence performance of the organization support adoption). It should be noted that models of this type are based on the assumption that championing behaviors of manufacturing managers ultimately result in higher levels of technology adoption.

The empirical evidence collected during their study of 32 manufacturing managers in the automotive parts industry indicates that top management endorsement of new technologies is a key factor in fostering managerial familiarization with new technologies. Not surprisingly, the study also showed that personal beliefs of manufacturing managers about the benefits of technology adoption affect the promotion of new technologies to other people in the organization.

The Dimnik and Johnston study revealed that when the manufacturing managers believed their subordinates held positive attitudes towards the adoption of the new technology, they became less active in their championing. Also, while the study supported the importance of top management's championing of new technologies, the support appears to be more important in "...legitimizing familiarization activities than providing the power to promote" the new technology (p. 161).

2.14 Conclusion

Most of the technology adoption literature focuses on characteristics of the firm or of the primary decision-maker that are positively related to the adoption (or early adoption) of new technologies. Marketing literature has extended this focus by identifying characteristics of the technology supplying industry and the technology adopting industry that appear to enhance the likelihood of rapid technology adoption. Manufacturing and marketing studies have included identification of a number of expected benefits firms hope to gain by adopting new technologies. Likewise, the math models developed to model the effects of these factors focus on the outcome of adoption. Most of these studies assume that the adoption of the technology being studied will be beneficial to the firm. However, very few of the studies investigate factors that manufacturers identify as risks prior to making the adoption decision especially if the outcome is to reject the technology. As Gatignon and Robertson (1989) point out, "[r]ejection behavior seems to be a different form of behavior [from adoption behavior] driven by a different set of factors." Since most of the adoption/diffusion literature pertains mainly to adoption only, conceptual research is needed to incorporate new considerations on the rejection decision.

Table 2.1. Characteristics of adopting firms

Reference	Type of technology	Characteristics found to be significant in predicting technology adoption
Kimberly and Evanisko (1981)	Technological innovations related to the diagnosis and treatment of disease in a hospital environment	Firm size (+) Education (+) Decentralized decision making (+) Competitive intensity (+) Firm age (+) Located in urban areas (+)
Kimberly and Evanisko (1981)	Administrative innovations related to the accounting, admissions, payroll, and patient records in a hospital environment	Firm size (+) Education (+) Cosmopolitan (+) Competitive intensity (+)
Feder and Slade (1984)	Zinc sulphate, seed treatment, pesticides, and weedicides in rice production	Firm size (+) Education (+) Information access (+) External communication (+)
Rahm and Huffman (1984)	Reduced tillage	Firm size (+) Education (+)
Wozniak (1984)	Monensin sodium, a livestock feed additive for increased weight gain in beef cattle	Firm size (+) Education (+) Information access (+) External communications (+)
Gatignon and Robertson (1989)	Laptop computers for the salesforce	Vertical coordination of supplier industry (+) Concentration ratio of adopter industry (+) Competitive price intensity in adopter industry (-) Supplier incentives (+) Decision maker has a preference for negative information (+) Decision maker's access to personal information (+)
Harper et al. (1990)	Sweep net and treatment thresholds for eliminating rice stink bug	Education (-) Technical experience (+) Information access (+)
McIntosh et al. (1990)	Soil conservation practices: reduced tillage, soil testing, crop rotation, strip cropping and contour plowing	Firm size (+) Education (+) Functional differentiation (+) Centralization of decision making (-) Technical experience (+)
Hodges and Cubbage (1990)	Improved land management practices on non-industrial privately owned forests	Experience (+) Firm size (+) External communications (+) Professional organization membership (-)
Keefe (1991)	Advanced manufacturing process technologies in the nonelectrical machine manufacturing industry	Firm size (+) Shift work (+)

Table 2.1. continued

Reference	Type of technology	Characteristics found to be significant in predicting technology adoption
Lin (1991)	Hybrid rice	Firm size (+) Education (+) Experience (+)
Baker (1992)	Computers in non-farm agribusinesses	Firm size (+) Firm type
Levin et al. (1992)	Optical scanners in grocery stores	Store size (+) Number of stores in firm (-) Market share (+) Competitive intensity (-) Competitors' technology (+) Per capita income (-)
West and Sinclair (1992)	Advanced manufacturing technologies in wood household furniture manufacturing	Firm size (+) Price of product (+) External communications (+) Cosmopolitanism measured by international travel (+) Professionalism (+) Contact with other firms (+) Number of engineering professionals (+)
Goodwin and Schroeder (1994)	Forward-pricing methods	Firm size (+) Experience (-) Crop production intensity (+) Education (+)
Saha et al. (1994)	bST (bovine somatotropin), a yield-enhancing growth hormone to increase milk production in dairy cattle	Firm size (+) Education (+)

Chapter 3. Problem Formulation and Solution Methodology

3.1 Overview

The primary purpose of this research was to develop a model of technology adoption decision making that integrates characteristics and risk factors that impact a firm's decision regarding the adoption and rejection of new technologies. Research in this area has been minimal since non-adoption of a technology does not necessarily imply rejection of that technology. It simply means that the forces pushing against technology adoption have not been overcome by forces pushing towards technology adoption. While Gatignon and Robertson (1989) found a few variables that seemed to help explain rejection behavior, their primary conclusion (with respect to rejection behavior) was that rejection behavior is not driven by the same factors that drive adoption behavior. They went on to say that "[g]iven that the long-run success of an innovation depends on both adoption and rejection, research to explore rejection and its determinants would have an applied significance yet untapped by diffusion researchers" (p. 47). Kimberly and Evanisko (1981) suggested that of particular interest would be those factors that drive exnovation, the process through which an organization decides to divest itself of innovation that it had previously adopted. Unfortunately, one issue that is often overlooked in the study of technology adoption is the fact that adoption of one innovation may be made possible by another's exnovation (Kimberly and Evanisko 1981).

Most studies discussing technology adoption concentrate on quantifiable measures or characteristics of the firm, decision-maker, or competitive environment. They reduce adoption behavior to a function of a set of these characteristics without considering the decision-maker's perceptions of the expected benefits or risks of adoption. These studies tend to ignore the effects of the evaluation and persuasion phases of the adoption decision process. In fact, one conclusion of Harper et al.'s (1990) study was that despite the importance of firm characteristics, decision-maker characteristics and technology characteristics, there was "...a need for more in-depth analysis of producers' perceptions of the net economic consequences of adopting or not adopting" new technology (p. 1004). This research extended this suggestion to include non-economic consequences of adoption or non-adoption and focused on the evaluation and persuasion phases of the adoption/rejection decision process.

In this chapter, a model of the adoption/rejection decision process is proposed. Special attention and detail are given to the evaluation/trial and persuasion phases since this is the core of the decision process. Use of the Analytic Hierarchy Process to model the evaluation/trial and persuasion phases is described in detail to illustrate the function of risk factors in the adoption/rejection decision process. Next, a methodology for validating the proposed model is outlined. A set of proposed risk factors and characteristics are described and their hypothesized effects on the adoption/rejection decision are discussed. Means for the measurement of these risk factors and characteristics via a mail survey are outlined. Finally, analysis techniques for interpreting data collected through the mail survey are summarized.

3.2 The adoption/rejection decision process model

Since the adoption decision process, as described in chapter 1, is a multi-phase process, any model of that process should also have multiple phases. A flow chart representation of this process is given in Figure 3.1. This technology adoption/rejection process model combines and extends the works of Muth and Hendee (1980), Rogers (1983), Puto et al. (1985), Meredith (1987), Ram (1987), Wiarda (1987), Gatignon and Robertson (1989), and Saha et al. (1994). The manner in which these earlier works combine with the efforts of this research is depicted in Figure 3.2. Component parts of models suggested by Muth and Hendee (1980), Rogers (1983), Puto et al. (1985), Ram (1987), and Gatignon and Robertson (1989) contribute to the technology adoption/rejection decision process as shown in Figure 3.2. Saha et al. (1994) provide the basis for the mathematical representations of the knowledge/awareness phase.

Despite the clear distinction of the influences of risk factors and characteristics implied in Figure 3.2, there could be some overlap in the interpretation of each of these sets of variables. For example, a firm's past experience with new technologies in general may influence adoption/rejection behavior, and would be considered a firm characteristic. Also, a firm's past experience with specific technologies similar to the one being considered may influence adoption/rejection behavior and might be considered more of a technology-dependent risk factor.

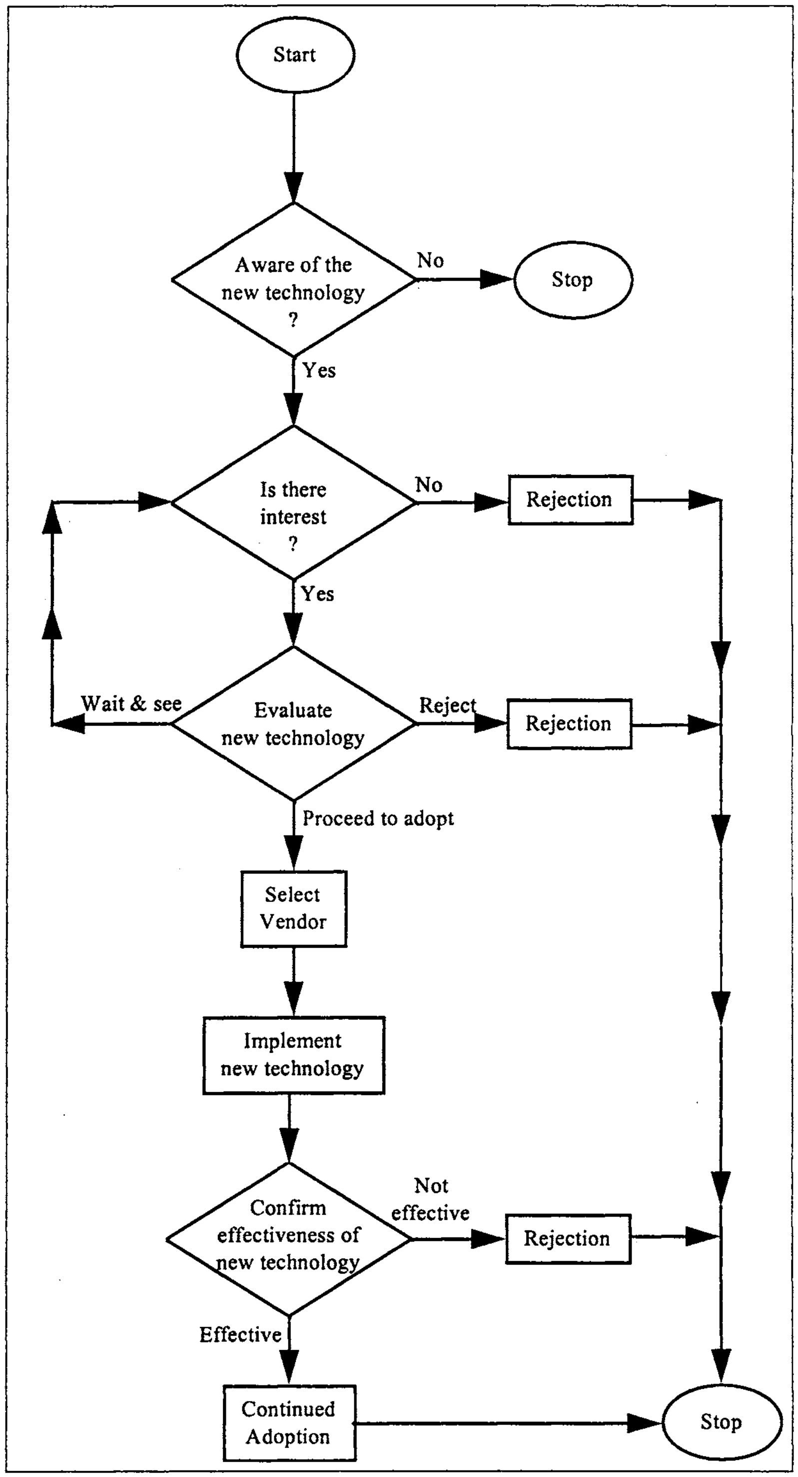

Figure 3.1. Flow chart of the technology adoption/rejection decision process

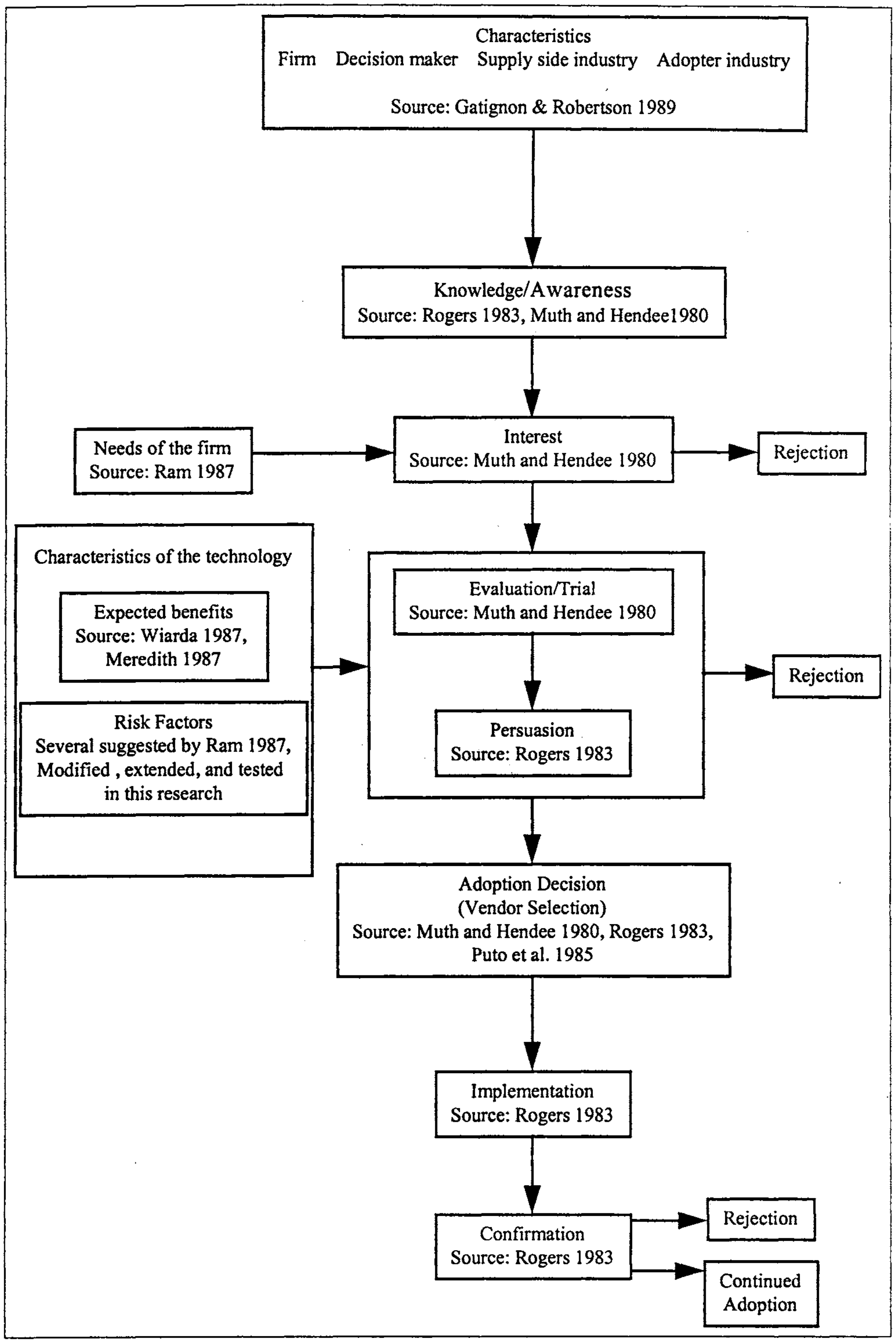

Figure 3.2. Main components of technology adoption/rejection decision process model

3.2.1 Knowledge/awareness

The knowledge/awareness phase occurs when an individual first becomes aware of a technology's existence and gains some understanding of how it functions, but technical details need not be included. In this phase, a manufacturer's acquired information level determines whether or not he/she has heard about the technology. Hearing about an innovation is very likely to be related to characteristics such as firm size and communication openness within an industry. If this is true, then a manufacturer's information level regarding a particular technology could be considered a function of *characteristics*.[13]

So, let the scalar i_{0m} represent the minimal information level at which knowledge/awareness of technology m occurs. Also, let **d** represent a vector containing relevant demographic characteristics, firm characteristics, decision-maker characteristics, adopter industry characteristics and supplier industry characteristics. This model assumes that a manufacturer's information level about technology m (a scalar value) may be a function of the elements of vector **d**. If $i_m(\mathbf{d})$ represents a manufacturer's information level about technology m, then a manufacturer is aware of technology m if $i_m(\mathbf{d}) \geq i_{0m}$. (Note: $i_m(\mathbf{d}), i_{0m} \geq 0$.)

3.2.2 Interest

The interest phase occurs when the individual seeks more information about the technology and considers if and how it applies to him/her and his/her firm. Therefore, the interest phase can only occur if the manufacturer is aware of the technology (i.e. $i_m(\mathbf{d}) \geq i_{0m}$).

Let:

$\mathbf{c}_m$	= a vector describing the characteristics of technology m
$i^*_m(\mathbf{c}_m)$	= all the information available regarding technology m ($i^*_m(\mathbf{c}_m) > i_{0m}$)
k_m	= the level of interest a manufacturer has in technology m ($k_m \geq 0$)
k_{0m}	= interest threshold of technology m
f	= a vector describing the needs of the firm.

[13]There may be some influence from the communicability of the technology also, but Saha et al. (1994) suggest that the primary emphasis will be the variables designated as characteristics.

If $i_{0m} \leq i_m(d) \leq i^*_m(c_m)$, then it is assumed that interest exists and $k_m > k_{0m}$.[14] During this phase, $i_m(d)$ approaches $i^*_m(c_m)$. As this happens k_m may increase or decrease indicating that the information is making the technology look more appealing or less appealing (Figure 3.3). The resulting interest level at the end of this phase may be considered a function *g* of the characteristics of the technology, the information level of the firm and the needs of the firm ($k_m = g(c_m, i_m(d), f)$). At the end of this phase, either the decision-maker proceeds to the next step or rejects the idea of adoption at that time. This decision is based on whether or not the interest of the firm in technology m is greater than some minimum interest threshold. So, if $k_m <= k_{0m}$, then adoption does not occur at this time, otherwise $k_m > k_{0m}$ and adoption might occur.

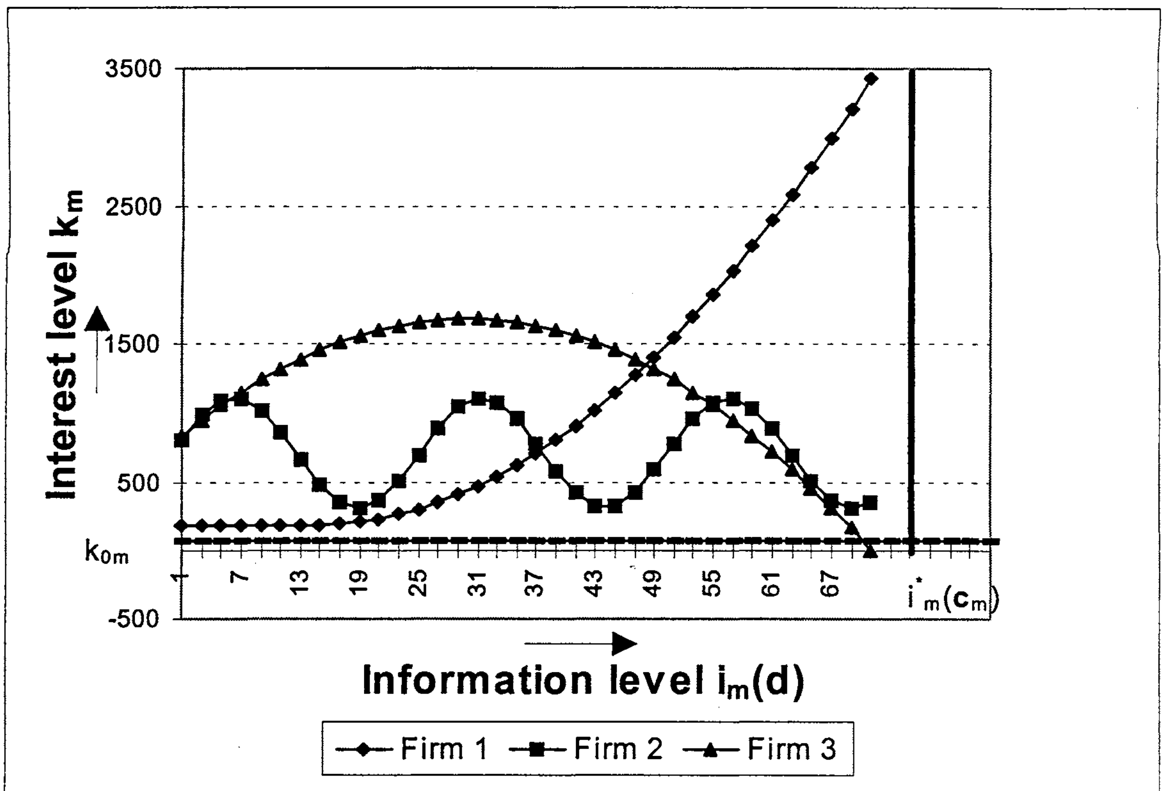

Figure 3.3. Changes in interest level as information level increases (3 different cases)

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[14]There may be some influence from the education of the decision-maker, the accessibility to information, and the communication openness of the industry, but it is believed that the main impact will come from characteristics of the technology and how well that technology matches up with the needs of the manufacturer.

Since interest is conditional on awareness,

$$p(k_m > k_{0m} | i_m(d) < i_{0m}) = 0$$
$$p(k_m > k_{0m} | i_m(d) \geq i_{0m}) > 0.$$

3.2.3 Evaluation/trial and persuasion

As described in chapter 1, the evaluation/trial phase of the adoption decision process focuses on the weighing of the benefits and costs of the proposed technology. The persuasion phase consists of the individual forming a favorable or unfavorable opinion of the technology. Here, these are difficult, if not impossible, to separate. Evaluation of a technology in order to decide whether to adopt the technology, reject the technology or wait for more information involves consideration of several non-commensurate elements. On a most basic level, the decision comes down to weighing the benefits of adopting the technology against the risks factors against adopting the technology. Figure 3.4 depicts graphically a proposed hierarchy of the risk factors and benefits of technology adoption.

One source of difficulty when evaluating a technology may be knowing what attributes of the technology contribute to the risks of adoption and what attributes of a technology contribute to the benefits of adopting the technology. The majority of studies in the technology adoption literature concentrate on characteristics and expected benefits that drive adoption behavior (i.e. those characteristics and expected benefits that lead to adoption of a technology). These characteristics and expected benefits comprise the left side of the hierarchy given in Figure 3.4. Risk factors that lead to technology rejection have been studied very little and thus, comprise the main thrust of this research. A proposed set of these factors is found in the right side of the hierarchy given in Figure 3.4.

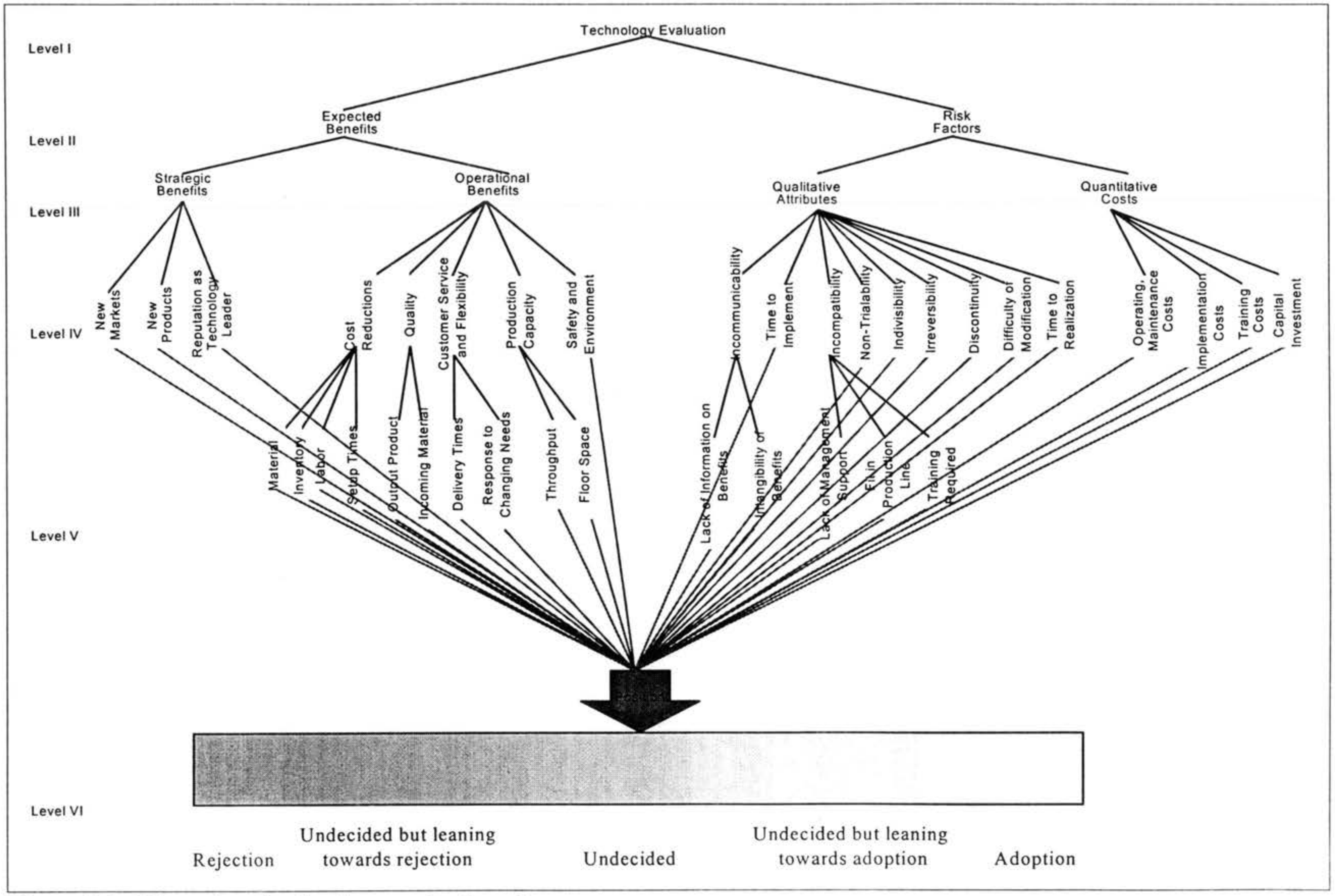

Figure 3.4. Hierarchy of technology evaluation phase

3.2.3.1 The Analytic Hierarchy Process

Use of the Analytic Hierarchy Process (Saaty 1980, 1982 in Canada and Sullivan 1989) to illustrate the evaluation/trial and persuasion phases of the adoption decision process is particularly appropriate because the process can structure a complex, multiattribute (including quantitative and qualitative attributes) hierarchically. The Analytic Hierarchy Process (AHP) decomposes the overall objective or focus into attributes. These attributes are further decomposed into sub-attributes, which in turn, are decomposed into sub-subattributes (and so on).

Once the problem is decomposed, pairwise comparisons of all elements (attributes, subattributes, sub-subattributes, etc.) on a given level are made with respect to the related elements in the level just above. These pairwise comparisons are then aggregated through eigenvalues to arrive at a priority weight (score) for each alternative. The alternative with the most attractive score is the one that should be selected.

Canada and Sullivan (1989) summarize the solution process as three stages with an optional concurrent fourth stage:

> 1. Determine the relative importance of the attributes and subattributes, if any;
>
> 2. Determine the relative standing (weight) of each alternative with respect to each subattribute, if applicable, and then successively with respect to each attribute;
>
> 3. Determine the overall priority weight (score) of each alternative; and
>
> 4. Determine indicator(s) of consistency in making pairwise comparisons (p. 262).

The proposed full-scale hierarchy (Figure 3.4) consists of six levels. The overall objective or focus is to evaluate a particular technology and is considered Level I. The proposed primary attributes of the evaluation phase are expected benefits and risk factors. These comprise Level II. "Expected benefits" is decomposed into the subattributes of strategic benefits and operational benefits. "Risk factors" is decomposed into the subattributes of qualitative concerns and quantitative costs. Strategic benefits, operational benefits, qualitative concerns, and quantitative costs make up Level III. This decomposition continues through one or two more levels, depending on the subattribute. The different outcomes or alternatives of the evaluation phase comprise Level VI. In this case, the outcomes were approximated by five categories: 1) adopt the new technology being evaluated, 2) lean towards adopting the new technology being evaluated, 3) reject the new technology being evaluated, 4) lean towards rejecting the new technology being evaluated, and 5) assume a neutral attitude towards the technology being evaluated ("wait and see"). One major assumption of the AHP is that the elements in each level are assumed to be independent. Since elements within a level are compared with one another, the level of detail of each element within a level was roughly the same.

Proposed expected benefits were based on results of past surveys of various industries[15] while the proposed risk factors were based on suggestions provided by various authors in the current literature. At each level, both proposed expected benefits and proposed risk factor lists were augmented by information collected during conversations held between the researcher and various wood products plant managers and owners (primarily in Virginia and North Carolina) over the last three years.

Since this research focused on identification of risk factors and their relative importance in the evaluation of new technologies, a subset of the proposed hierarchy was proposed as shown in Figure 3.5. The subset hierarchy consisted of four levels and had the objective of evaluating the qualitative attributes of the technology being considered.

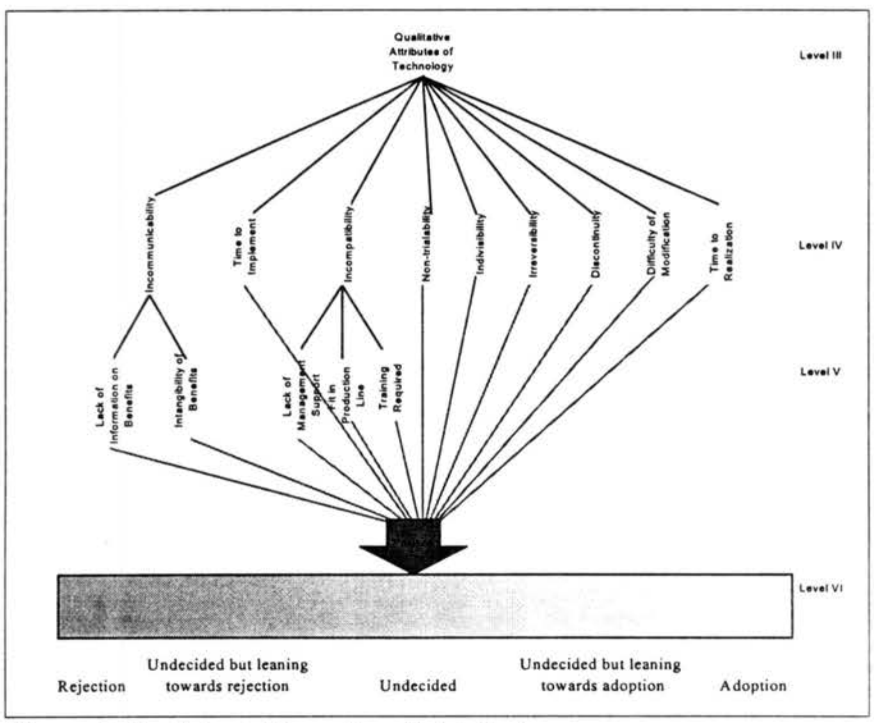

Figure 3.5. Subset hierarchy of risk factors

[15]Despite being identified through empirical studies, expected benefits are rarely incorporated into models that attempt to explain adoption/rejection behavior.

Once the hierarchy has been constructed, pairwise comparisons would be made between all the elements on a given level. To reduce the size of the example presented here, the number of alternative outcomes was reduced from five to three. The degree of preference, importance, or likelihood of each choice for each pairwise comparison is quantified on a scale of 1 to 9. Table 3.1 demonstrates how the scale would be applied when comparing element x to element y. Even numbers (2, 4, 6, 8) can be used to show compromises among the preferences given in Table 3.1. Inverse comparisons (where y is compared to x) result in the reciprocal of the preference number assigned when x is compared to y.

Table 3.1. Pairwise comparison scale for the Analytic Hierarchy Process (Source: Canada and Sullivan 1989, Smith 1994)

If x is . . . as (than) y,	then the preference number to assign is:
equally important/preferred/likely	1
weakly more important/preferred/likely	3
strongly more important/preferred/likely	5
very strongly more important/preferred/likely	7
absolutely more important/preferred/likely	9

In the proposed hierarchy of Figure 3.5, Level V elements that would be evaluated with respect to the Level IV element of Incompatibility would be Lack of Management Support, Fit in Production Line, and Training Required. Let A be the set of elements being compared and let each element be represented by a_i, $i = 1, 2$, or 3. The preference number assigned to a comparison of a_i to a_j ($i \neq j$) will be called c_{ij}. A comparison of a_j to a_i would then result in $c_{ji} = 1/c_{ij}$. By definition, a comparison of a_i to a_j where $i = j$ would result in the preference number 1. The matrix of pairwise comparisons of the Level V elements with respect to Incompatibility is given in Table 3.2.

Table 3.2. Pairwise comparisons of Level V elements with respect to Incompatibility

Level with respect to: Incompatibility		y: a_1 Lack of Management Support	y: a_2 Fit in Production Line	y: a_3 Training Required
V	x			
	a_1 Lack of Management Support	1	c_{12}	c_{13}
	a_2 Fit in Production Line	$1/c_{12}$	1	c_{23}
	a_3 Training Required	$1/c_{13}$	$1/c_{23}$	1

After obtaining the pairwise comparisons, priorities or weights for all of the elements are obtained by computing the eigenvector of the matrix of paired comparisons and then normalizing it to sum to 1.0. For the example given in Table 3.2, the relative priority weights for Management Support, Fit in Production Line, and Training Required would be $r_{1,2,1,1}$[16], $r_{1,2,1,2}$, and $r_{1,2,1,3}$, respectively ($r_{1,2,1,1} + r_{1,2,1,2} + r_{1,2,1,3} = 1.0$).

Consistency among the pairwise comparisons is evaluated using a consistency ratio. Canada and Sullivan (1989) explain the consistency ratio:

> The consistency ratio (C.R.) Is an approximate mathematical indicator, or guide, of the consistency of pairwise comparisons. It is a function of what is called the "maximum eigenvalue" and size of the matrix (called a "consistency index") which is then compared against similar values if the pairwise comparisons had been merely random (called a "random index"). If the ratio of the consistency index to the random index (called a "consistency ratio") is no greater than 0.1, Saaty suggests the consistency is generally quite acceptable for pragmatic purposes (p. 283).

If the consistency of the paired comparisons is deemed appropriate, then pairwise comparisons of each of the alternatives with respect to each of the attributes to which they relate are made. An example is provided in Table 3.3.

[16] $r_{1,2,1,1}$ denotes the relative priority of the first sub-sub-subattribute of the first sub-subattribute of the second subattribute of the first attribute.

Table 3.3. Pairwise comparisons of alternatives with respect to Lack of Management Support

Level with respect to:	Lack of Management Support	y: a_1 Wait and see	a_2 Proceed to adopt technology	a_3 Reject new technology
VI	x			
	a_1 Wait and see	1	c_{12}	c_{13}
	a_2 Proceed to adopt technology	$1/c_{12}$	1	c_{23}
	a_3 Reject new technology	$1/c_{13}$	$1/c_{23}$	1

Priority weights are calculated and the consistency of the pairwise comparisons checked as before. Priority weights calculated for "Wait and see", "Proceed to adopt new technology", and "Reject new technology" with respect to "Incompatibility" will be denoted by $p_{1,2,1,1,1}$[17], $p_{1,2,1,1,2}$, and $p_{1,2,1,1,3}$. Paired comparisons of alternatives with respect to the other sub-attributes of "Incompatibility" would be conducted and the subsequent priority weights calculated. These weights are then aggregated to arrive at a priority weight for each alternative. A summary of these priority weights and their aggregation is given in Table 3. 4.

Table 3.4. Aggregating priority weights for Incompatibility

	Compatibility: Lack of Management Support	Fit in Production Line	Training Required	Alternative priority weight
	$r_{1,2,1,1}$	$r_{1,2,1,2}$	$r_{1,2,1,3}$	
Alternative				
Wait & see	$p_{1,2,1,1,1}$	$p_{1,2,1,2,1}$	$p_{1,2,1,3,1}$	$\sum_i p_{1,2,1,i,1} r_{1,2,1,i} = p_{1,2,1,1}$
Proceed to adopt new	$p_{1,2,1,1,2}$	$p_{1,2,1,2,2}$	$p_{1,2,1,3,2}$	$\sum_i p_{1,2,1,i,2} r_{1,2,1,i} = p_{1,2,1,2}$
Reject new	$p_{1,2,1,1,3}$	$p_{1,2,1,2,3}$	$p_{1,2,1,3,3}$	$\sum_i p_{1,2,1,i,3} r_{1,2,1,i} = p_{1,2,1,3}$

[17]The priority $p_{1,2,1,1,1}$ represents the weight of the first alternative with respect to the first sub-sub-subattribute of the first sub-subattribute of the second subattribute of the first attribute.

The aggregation process continues up the hierarchy (to Level I). Tables 3.5 - 3.7 demonstrate this process.

The result of this aggregation process is a final set of priority weights for each alternative (in this example, p_1, p_2, and p_3). The alternative with the most desirable priority is the alternative that should be chosen.

By looking at the evaluation phase of the technology adoption decision process in this manner, it becomes apparent that manufacturers who adopt a particular technology are going to place different priorities on various attributes and sub-attributes than those who do not adopt that particular technology. This may be particularly true at lower levels of the hierarchy (e.g. Levels II and III in Figures 3.4 and 3.5). It is not possible to determine if the result of the evaluation phase will be adoption, rejection, or undecided a priori; therefore, identification of those attributes and sub-attributes that are significant in explaining adoption, rejection, and undecided behavior serves to ensure that a comprehensive set of factors is included in the evaluation process. This applies also to the case modeled by five alternative outcomes.

In summary, then, what *are* the attributes that explain adoption, rejection and undecided behavior? Phrased another way, which attributes are significant in predicting the outcome in the technology evaluation phase?

Table 3.5. Aggregating priority weights for Qualitative Attributes

	Qualitative Attributes									
	Incmp	TTI	Incom	N-trial	Indiv	Irrev	Disc	DoM	TTR	Alternative priority weight
	$r_{1,2,1}$	$r_{1,2,2}$	$r_{1,2,3}$	$r_{1,2,4}$	$r_{1,2,5}$	$r_{1,2,6}$	$r_{1,2,7}$	$r_{1,2,8}$	$r_{1,2,9}$	
Alternative										
Wait & see	$p_{1,2,1,1}$	$p_{1,2,2,1}$	$p_{1,2,3,1}$	$p_{1,2,4,1}$	$p_{1,2,5,1}$	$p_{1,2,6,1}$	$p_{1,2,7,1}$	$p_{1,2,8,1}$	$p_{1,2,9,1}$	$\sum_i p_{1,2,i,1} r_{1,2,i} = p_{1,2,1}$
Proceed to adopt new	$p_{1,2,1,2}$	$p_{1,2,2,2}$	$p_{1,2,3,2}$	$p_{1,2,4,2}$	$p_{1,2,5,2}$	$p_{1,2,6,2}$	$p_{1,2,7,2}$	$p_{1,2,8,2}$	$p_{1,2,9,2}$	$\sum_i p_{1,2,i,2} r_{1,2,i} = p_{1,2,2}$
Reject new	$p_{1,2,1,3}$	$p_{1,2,2,3}$	$p_{1,2,3,3}$	$p_{1,2,4,3}$	$p_{1,2,5,3}$	$p_{1,2,6,3}$	$p_{1,2,7,3}$	$p_{1,2,8,3}$	$p_{1,2,9,3}$	$\sum_i p_{1,2,i,3} r_{1,2,i} = p_{1,2,3}$

Incmp = Incompatibility
TTI = Time to implement
Incom = Incommunicability
N-trial = Non-Trialability
Indiv = Indivisibility
Irrev = Irreversibility
Disc = Discontinuity
DoM = Difficulty of modification
TTR = Time to realization

Table 3.6. Aggregating priority weights for Global Risks

	Global Risks		
	Quantitative Costs	Qualitative Attributes	Alternative priority weight
	$r_{1,1}$	$r_{1,2}$	
Alternative			
Wait & see	$p_{1,1,1}$	$p_{1,2,1}$	$\sum_i p_{1,i,1}r_{1,i} = p_{1,1}$
Proceed to adopt new technology	$p_{1,1,2}$	$p_{1,2,2}$	$\sum_i p_{1,i,2}r_{1,i} = p_{1,2}$
Reject new technology	$p_{1,1,3}$	$p_{1,2,3}$	$\sum_i p_{1,i,3}r_{1,i} = p_{1,3}$

Table 3.7. Aggregating priority weights for Technology Evaluation

	Technology Evaluation		
	Global Benefits	Global Risks	Alternative priority weight
	r_1	r_2	
Alternative			
Wait & see	$p_{1,1}$	$p_{2,1}$	$\sum_i p_{i,1}r_i = p_1$
Proceed to adopt new technology	$p_{1,2}$	$p_{2,2}$	$\sum_i p_{i,2}r_i = p_2$
Reject new technology	$p_{1,3}$	$p_{2,3}$	$\sum_i p_{i,3}r_i = p_3$

The multinomial choice (logit) model can be used to check how well a set of attributes predicts the outcome of the evaluation phase (McFadden 1974, Gatignon and Robertson 1989).

It is suggested in this research that when a firm is aware of and interested in a technology, the firm begins to evaluate the technology for use within its own operations. At the end of this evaluation, the firm may still be undecided about the technology and adopt a "wait and see" approach to acquiring the technology or it may choose to reject the technology or to adopt the technology. While these three outcomes have been used to approximate a continuum of adoption/rejection behavior in one study (Gatignon and Robertson 1989), the continuum may be approximated even more clearly with the addition of two other outcomes: undecided but leaning towards adoption and undecided but leaning towards rejection for a total of five possible outcomes (Figure 3.6). Consideration of other degrees of "undecidedness" would restrict the usefulness of the multinomial choice (logit) model because application of the model should be limited to situations where the possible outcomes can plausibly be assumed to be distinct (McFadden 1974).

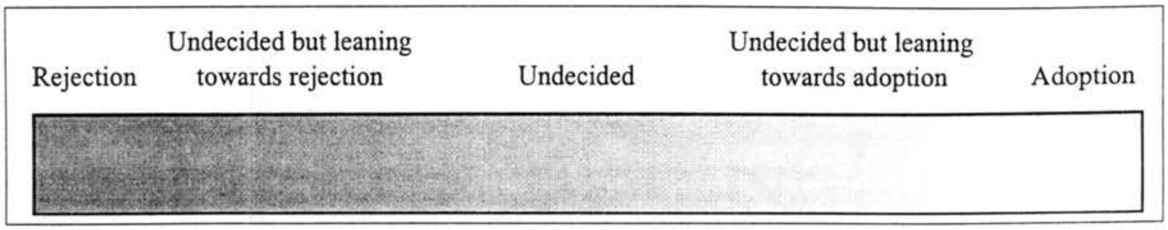

Figure 3.6. Five step approximation of adoption continuum

Thus, if the set of possible outcomes is denoted as J, then J = {adoption, leaning towards adoption, undecided, leaning towards rejection, rejection} = $\{j_{-2}, j_{-1}, j_0, j_1, j_2\}$ = {-2, -1, 0, 1, 2 }. Any of the five outcomes can be used as a "benchmark" against which the other outcomes are compared. To explain the model, the undecided outcome was selected as the "benchmark" member of the set of outcomes and, as such, was denoted j_1 to ease the notation of the multinomial choice (logit) model.

A firm drawn at random for the population of wood furniture manufacturers will have certain characteristics and certain perceptions of the risk factors associated with a particular technology m. To simplify terminology during this discussion of the multinomial choice model, a firm's characteristics and perceptions of risk factors will be called firm attributes. These firm attributes may be represented by the vector $\mathbf{X}_m$; the subscript m denotes the technology being considered.

Given a firm's firm attributes, X_m, and the set of possible outcomes, J, what is the probability that a firm's outcome of the evaluation phase will be j_{-2}? j_{-1}? j_0? j_1? j_2? Using z_m to represent the actual outcome of a firm's evaluation of the technology m, the conditional probability of the outcome being any j_i ($j_i \in J$) may be represented as

$$P(j_i \mid X_m, J) = P(z_m = j_i \mid X_m, \{j_{-2}, j_{-1}, j_0, j_1, j_2\}).$$

The observed outcome (or choice) when selecting a firm at random can then be viewed as a drawing from a multinomial distribution with selection probabilities $P(j_i \mid X_m, J)$ for ($j_i \in J$) (McFadden 1974).

The general form of the multinomial choice model is

$$P(j_i \mid X_m, J) = \frac{e^{v(X_m, j_i)}}{\sum_{k=1}^{n} e^{v(X_m, j_k)}}$$

where the outcomes are numbered sequentially beginning with one, the nonstochastic function v can be interpreted as a "utility indicator" of "representative" firm attributes and n represents the number of alternative outcomes. This formula can be adopted for empirical analysis by specifying the functional form of the "representative" utility $v(X_m, j_i)$ (McFadden 1974). If v is assumed to be linear in unknown parameters and i is used to represent j_i ($j_i \in J$), then the function v could be described as:

$$v(X_m, i) = \beta_{0i} + X_m' B_i.$$

The utility of the benchmark outcome is 0. Thus, if undecided ($j_0 = 0$) is the benchmark,

$$v(X_m, 0) = \beta_{00} + X_m' B_0 = 0$$

where the intercept β_{00} must equal zero and the vector B_0 must equal the zero vector. The parameter vectors B_i (for i = -2, -1, 1, 2) may be estimated by maximizing the log likelihood function.

So, given the set of possible outcomes, J, and the benchmark of undecided (0), the multinomial choice model of the evaluation phase would be:

$$P(z_m = i \mid X_m) = \frac{e^{\beta_{0i} + X_m' B_i}}{e^{\beta_{0,-2} + X_m' B_{-2}} + e^{\beta_{0,-1} + X_m' B_{-1}} + e^{\beta_{00} + X_m' B_0} + e^{\beta_{01} + X_m' B_1} + e^{\beta_{02} + X_m' B_2}}$$

$$P(z_m = i \mid X_m) = \frac{e^{\beta_{0i} + X_m' B_i}}{1 + e^{\beta_{0,-2} + X_m' B_{-2}} + e^{\beta_{0,-1} + X_m' B_{-1}} + e^{\beta_{01} + X_m' B_1} + e^{\beta_{02} + X_m' B_2}}$$

where i = -2, -1, 0, 1, or 2 and B_i is the vector of coefficients representing the marginal utilities of each of the independent variables (attributes) for outcome j_i.

Since evaluation is conditional on positive interest, the model would become:

$$p(z_m = i \mid X_m \cap k_m > 0) = \frac{e^{\beta_{0i} + X_m' B_i}}{1 + e^{\beta_{0,-2} + X_m' B_{-2}} + e^{\beta_{0,-1} + X_m' B_{-1}} + e^{\beta_{01} + X_m' B_1} + e^{\beta_{02} + X_m' B_2}}$$

with $\beta_{00} = 0$ and $B_0 = 0$ (vector).

3.2.4 Adoption/rejection decision

The adoption/rejection decision occurs when an individual engages in activities that lead to adoption or rejection of the innovation. In the case where adoption behavior is considered to be measured on a continuum, the undecided category is present, but no action is taken other than a return to the interest phase.

If $z_m = -1$, 0, or 1, then the interest phase is revisited with $i_{0m} \le i_m(\mathbf{d}) \le i^*_m(\mathbf{c}_m)$, and $k_m > 0$ at the beginning of the phase.

If $z_m = 2$, then the technology is rejected and $k_m = 0$.

If $z_m = -2$, then activities commence that lead to the acquisition and implementation of the technology.

The primary decision becomes one of vendor selection. Puto et al. (1985) developed models of vendor selection where only one supplier is selected and where multiple suppliers were selected. Since vendor selection is not the main interest of this research, the assumption that these models adequately address this issue is made.

3.2.5 Implementation and confirmation

The implementation phase involves putting the technology to use and the confirmation phase determines if the adoption decision should be reversed. Evaluation of the impact of the forces that were perceived to be benefits and risks prior to the adoption and determination of unexpected benefits and risks take place.

3.3 Solution methodology

The proposed model contains risk factors that had not been empirically tested for significant effects on adoption/rejection behavior. To validate this model, data was collected and analyzed using statistical techniques.

Data for the model was obtained through a mailed questionnaire. The questionnaire asked for information regarding demographics, firm characteristics, technologies adopted, considered, and rejected, and the manufacturers' perceptions of the risk factors associated with the technologies.

Postcards announcing the questionnaire were mailed to a purchased mailing list of manufacturers in the South Central United States. Firms in Arkansas, Louisiana, Mississippi, Oklahoma, and Texas that are classified under the Standard Industry Classification (SIC) 2511, SIC 2517, SIC 2521, and SIC 2541 were targeted[18]. This mailing list was comprised of 665 manufacturers. Information included with the mailing list indicated that 213 (32%) of these manufacturers employ more than ten people. This is consistent with national figures for the wood household furniture industry. According to the Bureau of Census, only 32 percent of the establishments in SIC 2511 employ more than twenty people (USDC 1985). In addition to the address, the name of the primary decision maker within the company (president or plant manager) was indicated on the mailing list. All materials were mailed to these individuals. Two weeks later, the questionnaire itself accompanied by a personally signed cover letter was mailed to all firms that did not warrant an out-of-business or otherwise undeliverable status. Estimates from the information service providing the mailing list indicated that there is typically a loss of four to five percent due to undeliverable addresses and no longer existing businesses (Kwasnik 1997). A second survey and follow-up letter were sent to non-respondents three weeks after the initial mailing.

Response rates for mail surveys average around 15 percent (Malhotra 1993). Therefore, non-response bias is a concern when using surveys for data collection. Since it has been suggested that late respondents are similar to non-respondents, a sample of late respondents was used to determine non-response bias (Churchill 1987). Respondents answering to the follow-up mailing were compared with those responding to the initial survey on key demographic variables and the number of technologies adopted. A chi-square

[18]SIC 2511 - Wood household furniture; SIC 2517 - Wood TV, radio, phono and sewing cabinets; SIC 2521 - Wood office furniture; SIC 2541 - Wood office and store fixtures

goodness-of-fit test was expected to be used to determine if the proportion of later respondents falling within each category (e.g. regional location or single company vs. multi-company corporation) could be predicted from the responses of the earlier respondents. Differences between the number of production employees of earlier respondents and those of later respondents were tested for significance using t-tests. Similarly, differences between the number of technologies adopted between earlier respondents and later respondents were tested using t-tests.

The industry-wide surveys provided information on characteristics and perception differences that were believed to differentiate between adopters, rejecters, and "undecideds" of various technologies including those shown in Figure 3.5.

Earlier, the idea of an adoption continuum was suggested. The continuum was approximated using five possible outcomes of a technology adoption decision: adopt, lean to adopt, undecided (still considering), lean to reject and reject. Each of these outcomes was considered a measure of adoption resistance. Levels of adoption resistance were approximated as: adoption = -2, still considering but leaning towards adoption = -1, still considering but no strong feelings towards adoption or rejection yet = 0, still considering but leaning towards rejection = 1, and rejection = 2. Higher resistance indicated that the decision-maker is likely to be leaning towards technology rejection and lower resistance indicated that the decision-maker is likely to be leaning towards technology adoption.

Many of the factors that had been cited as possible factors in rejection behavior are technology dependent and deal with the customers' perception of the intensity of the factors (Ram 1987). A set of these factors was identified and the following describes how this set of factors was tested to see which factors (if any) explained variance in levels of adoption resistance.

A set of technologies pertinent to the wood furniture industry in the South Central United States was selected for study. This set was comprised of equipment technologies and "soft" technologies (technologies that are not necessarily embodied in specific equipment). Let the set **T** represent the technologies being studied; **T** = { equipment technology 1, equipment technology 2, ..., equipment technology n, "soft" technology 1, "soft" technology 2, ..., "soft" technology n} = $\{t_1, t_2, ..., t_n, t_{n+1}, ..., t_{2n}\}$ For each technology t_i in **T**, manufacturers were asked whether or not they are aware of the technology. If a manufacturer was aware of technology t_i, he/she was asked to indicate their level of adoption resistance to technology t_i. For each technology that a manufacturer was aware of, he/she was asked to "rate" the intensity of each factor. For each firm surveyed, the data in Table 3.8 was collected for each technology[19] in **T** of which the firm was aware.

Table 3.8. Data collection table

	Incompatibility	Discontinuity	Non-trialability	Indivisibility	Incommunicability	Irreversibility	Time to realization	Time to implementation	Difficulty of modification	Firm size	Technical progressiveness	Technical expertise	Experience	Adoption resistance
CNC machining														
Thin saw-kerf technology														
Water-based finishes														
Statistical process control														
Self-managed /cross-functional work teams														
PC-based production control														

In the following sections, the factors that were proposed as risk factors that might explain adoption/rejection behavior are discussed. For each factor a brief description is given, a hypothesis relating that factor to adoption resistance is given, and a means of measuring the factor level so the hypothesis could be tested is given. These hypotheses are summarized in Table 3.9 (p. 87).

3.3.1 Proposed risk factors (independent variables)

3.3.1.1 Incompatibility

Incompatibility is a risk factor that is characteristic of the technology. The opposite, compatibility was originally described as how well the technology "...is perceived as consistent with the existing values, past experiences and needs of the receiver" (Rogers and Shoemaker 1971). The definition has been extended to include consistency with "the lifestyle of the consumer" (Ram 1987). Further extending this definition from the consumer research arena to the manufacturing arena, this research suggests that consistency with

[19]Firm size, technical progressiveness, technical expertise and experience will only be collected once for each firm, since these characteristics are assumed to be independent of the technology being considered.

"the lifestyle of the consumer" could be analogous to consistency with the operation of the current production system. Therefore, incompatibility, the obverse of compatibility, was expected to vary not only between different technologies, but also among firms when considering a single technology.

Hypothesis 1: *The higher the perceived incompatibility of the technology, the higher the adoption resistance.*

To obtain some measurement of incompatibility, surveyed firms were asked to respond to the following questions:

This technology fits easily into our production facility.

Scale: Strongly disagree, disagree, neutral, agree, strongly agree

This technology would/did require a substantial amount of training.

Scale: Strongly disagree, disagree, neutral, agree, strongly agree

Using this technology is/was supported by upper management.

Scale: Strongly disagree, disagree, neutral, agree, strongly agree

Have you tried a technology similar to this technology in the past?

Scale: Yes, no

If yes, how satisfied were you with the ease of implementation of the similar technology?

Scale: Very dissatisfied, dissatisfied, neutral, satisfied, satisfied

If yes, how satisfied were you with the performance of the similar technology?

Scale: Very dissatisfied, dissatisfied, neutral, satisfied, satisfied

3.3.1.2 Discontinuity

Discontinuity is a perceived risk factor that deals with the disruptive influence initial implementation of a new technology will have on the current system. As cited in West (1990) and Smith (1994), Robertson (1971) describes innovations as continuous, dynamically continuous, and discontinuous.

> A continuous innovation has the least disrupting influence on established patterns; typically, it involves the introduction of a modified product rather than an entirely new one.

> A dynamically continuous innovation is more disruptive than a continuous one, but does not alter established behavioral patterns. Adoption requires major change in an area of behavior that is relatively unimportant to the person "applying" or "experiencing" the innovation. It may involve creation of a new product or the modification of an existing one.

> A discontinuous innovation requires establishment of new behavioral patterns. Adoption causes major changes in behavior in an area of importance to the person "applying" or "experiencing" the innovation. This type of innovation typically involves a new product.

Since this factor reflects the perception of the disruptive influence the proposed technology will have on current behavior patterns, discontinuity may vary not only between different technologies, but also among firms when considering a single technology. This factor was expected to be highly correlated with incompatibility. Table 3.10 provides a summary of expected correlations between the proposed factors.

Hypothesis 2: *The higher the level of discontinuity of a technology, the higher the adoption resistance.*

To obtain a measurement of discontinuity, responses from the following two questions were combined:

When considering this technology, how would/did you characterize it?

Scale: Completely new to the firm, modification or extension of current technology

When considering this technology, do/did you consider this a major change in the production process or a minor change in the production process?

Scale: Major change, minor change

These responses were combined to result in a discontinuity level measurement as shown in Figure 3.7. This scale was then translated to a -1 to 1 scale with level 1 being -1 and level 4 being 1.

	Completely new	Modification or extension
Major change	Level 4	Level 3
Minor change	Level 2	Level 1

Figure 3.7. Discontinuity measurement

3.3.1.3 Non-trialability

Non-trialability is a technology-dependent risk factor that deals with how difficult it is for the technology to be tried by the manufacturer prior to adoption and acquisition. Ideally, for a given factor, all surveyed firms would rate this factor identically. However, it was likely that there would be *some* variability among the firms being surveyed on the level of this factor that should be attributed to a certain technology. Assuming for a moment that this variability would be minimal, this factor's effect was expected to become apparent when analyzing adoption resistance using data reflecting a group (i.e. 2 or more) of technologies.

Hypothesis 3: *The higher the non-trialability of a technology, the higher the adoption resistance.*

To measure non-trialability, surveyed firms were asked to respond to:

There is/was sufficient opportunity to witness the operation/application of this technology prior to purchasing/applying it.

Scale: Strongly disagree, disagree, neutral, agree, strongly agree

This technology can be implemented and run in parallel with current technology.

Scale: Strongly disagree, disagree, neutral, agree, strongly agree

3.3.1.4 Indivisibility

Indivisibility is a risk factor characteristic of the technology that measures whether a new technology can or cannot be adopted/implemented in stages. Again, a particular technology's rating on this factor was expected to be very consistent among adopters, rejecters, and undecideds. As with non-trialability, the effect of this factor (if any) would become apparent when analyzing variation in adoption resistance levels between technologies. Since this factor is somewhat related to non-trialability, a high correlation between these two factors was expected.

Hypothesis 4: *The higher the indivisibility of the technology, the higher the adoption resistance.*

To measure this factor, surveyed firms were asked:

How easy is it to adopt this technology in stages?

Scale: Very difficult, difficult, average, easy, very easy

How easy is it to test this technology using simulation or off-line trials prior to adopting it?

Scale: Very difficult, difficult, average, easy, very easy

3.3.1.5 Incommunicability

Incommunicability refers to the degree to which a technology's attributes or benefits are incapable of being communicated to potential adopters. Therefore, incommunicability was considered technology-dependent. This variable consisted of two parts. The first part of this variable represented how well or how poorly the benefits of the technology are communicated to the manufacturer. This could be considered something akin to communication openness of the adopter industry. Communication openness of an industry may be measured by the availability of information in the industry via trade journals, conventions or trade shows, and industry association meetings. However, it would be reasonable to expect that in any industry, some technologies receive more attention in trade journals and at trade shows than others. Therefore, this factor is technology dependent.

Hypothesis 5: *The less readily available information on the technology, the higher the adoption resistance.*

To measure the unavailability of information regarding a technology's benefits, surveyed firms were asked to respond to the following question(s):

Information regarding this technology is readily available.

Scale: Strongly disagree, disagree, neutral, agree, strongly agree

How difficult is it for you firm to obtain information regarding the benefits of this technology?

Scale: Very difficult, difficult, average, easy, very easy

The second part of the variable incommunicability is the intangibility of the benefits of the technology. While some would argue that this characteristic is dependent entirely on the technology and does not involve the perceptions of the potential adopter, empirical results indicate otherwise. Surveys by Wiarda (1987) and Meredith (1987) for example, recognized variability in the benefits manufacturers expected specific technologies to produce. The actual benefits of any technology "depend on the situation in which it is used, how it is employed, its fit with existing processes, and so on" (Meredith 1987, p. 252). Therefore, the intangibility of the benefits of a given technology depends on the decision-maker's perception of what those benefits may be given the situation in which it would be used.

Hypothesis 6: *The higher the intangibility of the benefits of the technology, the higher the adoption resistance.*

To measure the intangibility of the expected benefits of a particular technology as perceived by the manufacturer, surveyed firms were asked:

What are the main benefits you would expect if you were acquired this technology?

Scale: Reduced costs, improved quality, improved communication

(The responses would be rated as: reduced costs - intangibility level 1; improved quality - intangibility level 2; improved communication - intangibility level 3.)

In general, the following hypothesis that combines Hypotheses 5 and 6 was proposed:

Hypothesis 7: *The higher the incommunicability of the technology, the higher the adoption resistance.*

3.3.1.6. Time to implementation

Time to implementation is a risk factor that represents the expected length of time between the time that the decision to acquire the technology is made and the time that the technology is fully implemented. This factor might be related to continuity and complexity.

Hypothesis 8: *The longer the time to implement, the higher the adoption resistance.*

Expected time to implementation was measured with the following question:

Suppose that today, you made the decision to obtain this technology for your plant. When do you think that the technology would be fully implemented?

Scale: Within a month, 1-3 months, 4-6 months, 7-12 months, more than a year

3.3.1.7 Time to realization

Realization is a risk factor that reflects the expected length of time that will pass before a firm begins to realize the benefits of the technology. It may take longer to *recognize* benefits less tangible than those that are more tangible, and thus, the manufacturer's perception may be that it takes longer to *realize* these benefits.

Hypothesis 9: *The longer the realization time, the higher the adoption resistance.*

To capture a measure of a manufacturer's expectations of the time to realization of benefits, surveyed firms were asked:

> Suppose you were to begin implementing this technology today, when would you expect to start seeing the expected benefits?
>
> Scale: Within a month, 1-3 months, 4-6 months, 7-12 months, more than a year

3.3.1.8 Difficulty of modification

Difficulty of modification is a technology-dependent risk factor that reflects how easily the technology can be modified to meet the firm's specifications. Since a manufacturer's perception of the difficulty with which a technology may be implemented may depend in part on how difficult it is to modify the technology to work with the current production system, a strong positive correlation between these two factors was expected.

Hypothesis 10: *The more difficult it is to modify a technology, the higher the adoption resistance.*

To determine the difficulty of modification of a technology, surveyed firms were asked:

> This technology could be easily modified to work with our production system.
>
> Scale: Strongly disagree, disagree, neutral, agree, strongly agree

3.3.1.9 Irreversibility

Irreversibility is a risk factor that denotes the lack of the option of being able to discontinue adoption of the technology if so desired. This factor may not be completely independent of the manufacturer though. The degree of risk aversity of a manufacturer and the technical progressiveness of the firm may impact his/her perception of the irreversibility of a technology.

Hypothesis 11: *The higher the irreversibility of a technology, the higher the adoption resistance.*

To measure the viability of discontinuing the use of a technology, should it be adopted (or after it was adopted), surveyed firms were asked to respond to the following questions:

> How would you characterize the lost time, money and effort spent on this technology should it prove to be ineffective for your plant?
>
> Scale: Very significant, significant, average, insignificant, very insignificant
>
> This technology would be difficult to abandon should it prove ineffective.
>
> Scale: Strongly disagree, disagree, neutral, agree, strongly agree

3.3.2 Proposed characteristics

Characteristics proposed here as impacting the technology adoption/rejection decision process reflect characteristics of the firm, the decision-maker or the competitive environment in which the firm operates. These characteristics are not technology dependent, but reflect a firm's willingness and ability to innovate.

A firm's willingness to innovate might be measured by the technical progressiveness of the firm and the firm's experience with past technological innovations.

A firm's ability to innovate might be measured by the firm size (a surrogate measure for capital resources) and the technical expertise the firm "possesses."

3.3.2.1 Technical progressiveness

Technical progressiveness is a characteristic of the firm that reflects the technology policy of an organization. Technical progressiveness refers to the degree to which a firm is committed to an innovative strategy within manufacturing.

Hypothesis 12: *The lower the technical progressiveness of the firm, the higher the adoption resistance.*

To measure the technical progressiveness of a firm, surveyed firms were asked to respond to the following questions:

> Our firm believes it is important to develop expertise on existing production technologies.
>
> Scale: Strongly disagree, disagree, neutral, agree, strongly agree

Our firm is willing to make plant space available for experimentation with new equipment.

Scale: Strongly disagree, disagree, neutral, agree, strongly agree

In the past year, how many trade shows has a representative from your firm attended?

3.3.2.2 Past experiences

Ram (1987) contends that "[t]he biasing influence of past experience that an individual brings to a present problem-solving or decision-making activity is known as 'mind set,' and mind-set plays an important role in shaping consumer perception and attitude formation" (p. 211). This can be extended to firms within a manufacturing industry.

Hypothesis 13: *The less favorable a manufacturer's experience with earlier technologies, the higher the adoption resistance.*

Surveyed firms were asked:

In general, how would you describe your firm's past experiences with new technology?

Scale: Not applicable, very disappointed, disappointed, neutral, pleased, very pleased

These characteristics could be aggregated into a measure of willingness to innovate and the following hypothesis could then be tested:

Hypothesis 14: *The more willing a manufacturer is to innovate, the lower the adoption resistance.*

However, in this research, the two characteristics were kept separate.

3.3.2.3 Firm size

Larger firms may have better access to capital for investment in technologies (Kimberly and Evanisko 1981, Meredith 1987, Baker 1992). Therefore, firm size was treated as a surrogate measure for capital resources.

Hypothesis 15: *The smaller the firm, the higher the adoption resistance.*

The measure for firm size was the number of production employees.

3.3.2.4 Technical expertise

As mentioned before, engineers often can understand the complexities of new technologies and thus, reduce the risk of adopting and implementing them (West 1990, West and Sinclair 1991, West and Sinclair 1992).

Hypothesis 16: *The higher the technical expertise within a firm, the lower the adoption resistance.*

Technical expertise was measured by:

How many manufacturing (process) engineers does your firm employ?

Combining the measures of firm size and technical expertise into a single measure of a firm's ability to innovate allows the testing of the following:

Hypothesis 17: *The poorer the ability of a firm to innovate, the higher the adoption resistance.*

Again, the two measures were kept separate for this research.

Table 3.9. Summary of hypotheses for which support is sought

Number	Hypothesis
1	The higher the perceived incompatibility of the technology, the higher the adoption resistance
2	The higher the level of discontinuity of a technology, the higher the adoption resistance.
3	The higher the non-trialability of a technology, the higher the adoption resistance.
4	The higher the indivisibility of the technology, the higher the adoption resistance.
7	The higher the incommunicability of the technology, the higher the adoption resistance.
8	The longer the time to implementation of a technology, the higher the adoption resistance.
9	The longer the realization time of a technology, the higher the adoption resistance.
10	The more difficult it is to modify a technology, the higher the adoption resistance.
11	The higher the irreversibility of a technology, the higher the adoption resistance.
12	The lower the technical progressiveness of the firm, the higher the adoption resistance.
13	The less favorable a manufacturer's experience with earlier technologies, the higher the adoption resistance.
15	The smaller the firm, the higher the adoption resistance.
16	The higher the technical expertise within a firm, the lower the adoption resistance.

3.3.3 Proposed analysis

Responses from the survey were analyzed at several different levels, each of which provides information on characteristics and risk factors that differentiate between adopters and rejecters. First, conclusions were drawn based on responses to questions with respect to all technologies. However, it is likely that this type of analysis would incorporate several different sources of variation. As mentioned before, the levels of the risk factors are dependent on the technology and involve the manufacturer's perceptions of the level the technology possesses of each factor. By analyzing the responses for each technology by itself, differences in perceptions of the factors as they relate to the particular technology by adoption resistance level were identified.

Second, it was expected that some factors such as communicability and divisibility would be perceived similarly regardless of whether the respondent is an adopter, a rejector, or an undecided. Differences in these factors as they apply to adoption and rejection behavior were determined through analysis of responses involving all of the technologies.

Third, differences in the factors that differentiate between adopters and rejecters may exist between equipment technologies and "soft" technologies. Therefore, analysis was conducted comparing responses to questions regarding all equipment technologies to responses to questions regarding all "soft" technologies.

Multinomial logit analysis results in a set of significant factors for each value the dependent variable can take on (i.e. each outcome of the decision process) compared to a benchmark value. The dependent variable in multinomial logit analysis is the probability that the decision firm i makes (with respect to a technology) is j where j $\in$ {adopt, lean to adoption, undecided, lean to rejection, reject} = {-2, -1, 0, 1, 2} given firm i's perceptions of the levels of all factors being tested. Assuming that the benchmark value is the undecided or neutral position, part of the results would be sets of risk factors and characteristics that impact the probability that a firm's decision will be adoption (-2) versus undecided (0) (set 1) or that the outcome will be lean to adoption (-1) versus undecided (0) (set 2). This analysis also provides sets of risk factors and characteristics that impact the probability that a firm's decision will be to reject the technology (2) versus undecided (0) (set 3) or lean towards rejecting the technology (1) versus undecided (0) (set 4). Any two of these sets may or may not be the same. The significant effects in sets 1 - 4 indicate support for the hypotheses or for the opposite of the hypotheses based on their effects (positive or negative) relative to the benchmark level. In other words, these are significant effects when considering two adoption resistance levels at a time. In addition, through analysis of variance, the multinomial logit analysis also results in a set of significant factors and characteristics that explain the variance among *all* the different levels of adoption resistance (set 5).

The fourth step in this analysis was comparing the results of the multinomial logit analyses to see if the same factors that predict rejection behavior can predict adoption behavior or "undecided" behavior. Predicted responses were compared with actual adopter classifications. In this instance, there are five adopter classifications and thus, the proportional chance criterion would predict that roughly 20 percent of the respondents would fall into each classification.

Table 3.10. Summary of expected correlations between risk factors

	Incomp	Discon	N-Tri	Indiv	Incom	TTI	TTR	DoM	Irrev
Incompatibility	1	++				- -	-	++	
Discontinuity		1				- -	-	++	
Non-trialability			1	+					
Indivisibility				1					+
Incommunicability					1		+		+
Time to implementation						1		- -	- -
Time to realization							1	- -	- -
Difficulty of modification								1	
Irreversibility									1

Incomp = Incompatibility
Discon = Discontinuity
N-Tri = Non-Trialability
Indiv = Indivisibility
Incom = Incommunicability
TTI = Time to implement
TTR = Time to realization
DoM = Difficulty of modification
Irrev = Irreversibility
++ = Highly correlated, positive correlation
- - = Highly correlated, negative correlation
\+ = Positive correlation
\- = Negative correlation

Chapter 4. Data Collection and Respondent Profile

4.1 Introduction

Simply put, the problem was one of identifying factors that affect technology rejection as well as technology adoption. Data to test the proposed model was obtained through a mailed questionnaire. The questionnaire asked for information regarding demographics; firm characteristics; technologies adopted, considered, and rejected; and the manufacturers' perceptions of the risk factors associated with the technologies. An explanation of the data collection method is given, followed by a profile summary of the firms responding to the questionnaire. The following chapter contains a discussion on the analysis of the data as it relates to technology rejection and technology adoption.

4.2 Methods

4.2.1 Determining the technologies

Since many of the factors hypothesized to affect technology adoption/rejection were technology dependent, a *set* of technologies rather than just a single technology was needed to ascertain the effects of the proposed risk factors. Because of the perceived differences between implementing hard technologies and implementing soft technologies, technologies representing both hard and soft technologies were included in the set.

A focus group meeting was held with several members of the Oklahoma Wood Manufacturers Association and members of the Agricultural Extension Service of Oklahoma. During this meeting, the relatively low level of technology being used in Oklahoma wood products firms was discussed and a list of potential technologies was developed. This list was compared to a list of the most frequently used wood processing equipment in Louisiana (Vlosky 1996), a list of wood processing equipment often found in Ohio, Kentucky, and West Virginia (Bumgardner 1995), and a list of wood processing technologies identified in an earlier nation-wide survey of the wood household furniture industry (West 1990). Additions to the list of technologies and deletions from the list were based on these comparisons. Finally, a set of technologies was presented to a group composed of academicians in industrial engineering and others knowledgeable of the U.S. wood products industry for final adjustment. The list of six technologies used in the survey included three hard technologies (thin saw-kerf technology, CNC machining, and water-based finishes) and three soft technologies (self-managed/cross-functional work teams, statistical process control, and PC-based production control systems).

4.2.2 Survey instrument

A questionnaire was developed based on the hypotheses and research questions presented in sections 3.1 and 3.2 of chapter three. It was reviewed by academicians and agricultural extension personnel. Additions to the questionnaire were suggested during this review process. Also, the questions themselves and the format of the questionnaire was reviewed by a forest products marketing specialist. The questionnaire was approved by the Oklahoma State University Institutional Review Board (a copy of the approval form is found in Appendix A).

Due to the sequence of events, pretesting of the questionnaire was limited. Surveys were given to a group of three wood products manufacturers and comments were solicited for improvements in instructions, question wording and format. Slight changes were made based on these comments; major changes were not made because the questionnaire had already been approved by the Oklahoma State University Institutional Review Board. A copy of the final questionnaire may be found in Appendix D.

Three questions in particular (questions 29, 35 and 36) seemed to cause concern for the pretest group. Two of these questions (questions 35 and 36) regarded past experiences with technologies similar to the technology in question. Pre-test respondents often felt that they were being asked about their experiences with the currently discussed technology. However, there were no suggestions for clarifying the wording of these questions. Therefore, responses to questions 35 and 36 were eliminated from the data to be analyzed. Pre-test respondents also had trouble differentiating between the question concerning availability of benefit information (28) and the question concerning the difficulty of obtaining information on each technology (29). Therefore, a high correlation between the responses to these questions was expected.

4.2.3 Sample frame

The sample frame for this survey consisted of a purchased mailing list of wood products manufacturers in the South Central United States. Firms in Arkansas, Louisiana, Mississippi, Oklahoma, and Texas that are classified under the Standard Industry Classification 2511, SIC 2517, SIC 2521, and SIC 2541 were targeted[20]. This mailing list was comprised of 665 manufacturers. A breakdown of the sample frame by state and number of employees is given in Table 4.1.

Table 4.1. Description of sample frame by state and number of employees.

Number of Employees	Arkansas	Louisiana	Mississippi	Oklahoma	Texas	Total	Percentage of Total (%)
0-10	63	35	38	38	307	481	72.3
11-25	8	4	12	8	59	91	13.7
26-50	3	2	3	3	15	26	3.9
51-100	7	3	5	3	15	33	5.0
101-250	8	2	4	1	4	19	2.9
251-500	5	0	4	1	1	11	1.7
501-1000	0	0	1	1	0	2	0.3
> 1000	2	0	0	0	0	2	0.3
Total	96	46	67	55	401	665	
Percentage of Total (%)	14.4	6.9	10.1	8.3	60.3		100.0

To confirm that the sample frame was representative of the wood products industry in the study region, comparisons of firm size were made between the sample frame and published figures for the Louisiana wood products industry and the Oklahoma wood products industry. In this case, firm size was measured as number of employees. Ideally, for this study, technology adoption and rejection rates would be the best measures for determining if the sample frame was representative of the wood products industry in the

[20] SIC 2511 - Wood household furniture; SIC 2517 - Wood TV, radio, phono and sewing cabinets; SIC 2521 - Wood office furniture; SIC 2541 - Wood office and store fixtures

South Central US. However, this information was unavailable and the surrogate measure of firm size was used. Firm size was selected as a means of comparison since earlier studies indicated that larger firm size was associated with a higher technology adoption rate (e.g., West 1990, Kimberly and Evanisko 1980).

Information included with the mailing list indicated that 111 (17%) of the 665 manufacturers employ more than twenty people and 93 (14%) employ more than 25 people. The 1996 Oklahoma Directory of Manufacturers and Processors listed 69 firms under the four SIC classifications targeted in the study. Sixty-five of these firms provided estimates of employee population within their firms. Of the 65 firms, 17% claimed more than 25 employees. Of the firms listed under SIC 2511, only 14% indicated that they had an employee population of more than 25. According to a study by the Louisiana Forest Products Laboratory, 27% of the wood products firms in the Louisiana secondary wood processing industry employ more than 10 employees (Vlosky and Harding 1995). Therefore, it was concluded that the sample frame adequately represented the wood products industry of the South Central United States, at least by firm size as measured by the number of employees.

4.2.4 Survey administration

Postcards announcing the questionnaire were sent to all firms in the sample frame. Approximately three weeks later, the questionnaire accompanied by a personally signed cover letter was sent to each firm in the sample frame. The postcard text and the questionnaire are provided in Appendices C and D. All correspondence was addressed to the primary decision maker within the company (president or plant manager) using the proper name supplied on the purchased mailing list. If a proper name was not supplied, correspondence was addressed to the vice-president of manufacturing. Postcards and surveys returned by the US Postal Service were categorized as undeliverable and these firms were removed from the sample frame. A second survey and follow-up letter were sent to non-respondents three weeks after the initial mailing. In addition, several firms were interviewed by telephone to ensure an adequate response rate. Firms were selected at random from the pool of non-respondents. However, the firms that were willing to participate in telephone interviews tended to be larger companies that were structured as corporations.

4.2.5 Survey response rate

Six hundred sixty-five firms were included in the initial sample frame. Sixty-five questionnaires were returned by the US Postal System because they were undeliverable. Thirty-seven surveys were returned with notes indicating that the firm was either not involved in manufacturing wood products (31) or it was no longer in business (6). The seemingly high proportion of undeliverables and out-of-business firms (71 out of 665) is consistent with nation-wide surveys of the wood household furniture industry and reflects an industry characterized by a large number of small firms and high fragmentation (West 1990). The firms to which these surveys were sent were eliminated from the sample frame, leaving 554 firms in the sample frame. Other surveys were returned with brief notes stating that this survey did not apply to their firm or that they did not have time to complete the survey. Since it was not possible to tell if these firms should or should not have been included in the sample frame, these responses were simply called refusals. Other surveys provided basic demographic information but no responses to any of the risk factor questions; these surveys were classified as not usable. All other surveys were considered usable. A summary of survey responses is given in Table 4.2.

Table 4.2. Questionnaire response rate summary.

Non-Deliverables		65
Responses		
Do not produce wood products	31	
Notes indicating out of business	6	
Do not do manufacturing	9	
Refused to respond because of time constraints	3	
Refused to respond because they did not feel the survey was applicable or did not provide usable data	9	
Usable responses	82	
Number of responses		140
Non-respondents		460
Total		665

4.2.6 Non-response bias

The response rate for this survey was 15 percent. Additional efforts for data collection were restricted since response rates for mail surveys average around 15 percent (Malhotra 1993). Because of this response rate, tests for non-response bias were conducted. To test for non-response bias, respondents answering the follow-up mailing were compared to those responding to the initial survey on key demographic variables and the number of technologies adopted. This approach has been used in previous research where it has been assumed that late respondents are similar to non-respondents (Churchill 1987, West 1990). Respondents to the second mailing of the survey can be considered a sample of the non-respondents to the first mailing of the survey. Thus, a comparison of respondents to the first mailing (early respondents) and respondents of the second mailing (late respondents) on key characteristics was used as an indication of non-response bias. Insignificant differences between the two groups would indicate that there is little non-response bias, and therefore, results of statistical analyses should be representative of the entire population of wood furniture manufacturers in the South Central United States.

Respondents answering the follow-up mailing were compared with those responding to the initial survey on key demographic variables and the number of technologies adopted. A paired t-test was conducted on firm size as measured by the number of employees. One outlier from each of the two samples (early respondents and late respondents) was removed, and a pooled estimate of the variance was used. The outliers were removed so the estimate of the variance would not be overly inflated. Since tests performed with larger variances typically result in fewer rejections of the null hypotheses, elimination of outliers strengthens the tests' ability to detect significant differences in the means. No significant difference between the mean firm size of the two samples was detected.

T-tests were also conducted on number of production employees, number of engineers, firm age and number of technologies adopted. A summary of t-test results is presented in Table 4.3. The number of technologies adopted was the only measure to indicate that non-response bias might exist. At the $\alpha = 0.05$ level, significant differences were detected between the average number of technologies adopted by early respondents and the average number of technologies adopted by late respondents with the late respondents adopting fewer technologies on average. This result is not surprising since manufacturers who have not adopted many of the six technologies may not feel as though the survey is applicable to them and thus, they may be less likely to complete and return the questionnaire, especially during the first mailing.

It was anticipated that a chi-square goodness-of-fit test would be used to determine if the proportion of later respondents falling within each category (e.g. regional location or single company vs. multi-company corporation) could be predicted from the responses of the earlier respondents. Survey results, however, produced a matrix characterized by many zero-valued cells. In this instance, the chi-square computed is likely to be an overestimate and even the application of Yates' correction for continuity fails to adequately adjust the computed chi-square (Downie and Heath 1965). Therefore, the Mann-Whitney U-test for medians was employed for each category.

The Mann-Whitney U-test is used with independently drawn random samples to test for differences in sample medians (Downie and Heath 1965). The sample sizes do not have to be the same. The Mann-Whitney U-test is a particularly useful substitute for the t-test when dealing with factors for which a value other than one of the ordinal values (such as an average is likely to have) would have no meaning. When at least one of the sample sizes is larger than 20, the U statistic is considered to be normally distributed and a standardized normal z ratio is calculated. Since the hypothesis is that of equal medians, the test is a two-tailed test.

Table 4.3. Summary of paired t-tests for non-response bias

Factor	Null hypothesis	Sample	Number of responses	Number of outliers removed	Sample average ($\bar{x}$)	Calculated t	p-value (2-tail)	Reject null hypothesis $\alpha = 0.05$
No. of employees	$\mu_1 = \mu_2$	Respondents to first mailing	48	1	36.89	-0.8583	0.3933	No
		Respondents to second mailing	34	1	54.52			
No. of production employees	$\mu_1 = \mu_2$	Respondents to first mailing	48	1	28.57	-1.2037	0.2323	No
		Respondents to second mailing	34	1	49.11			
Firm age (years)	$\mu_1 = \mu_2$	Respondents to first mailing	48	2	16.13	-0.4076	0.6847	No
		Respondents to second mailing	33	1	17.41			
No. of techs. adopted	$\mu_1 = \mu_2$	Respondents to first mailing	48	0	1.21	2.1995	0.0307	Yes
		Respondents to second mailing	34	0	0.65			
No. of engineers	$\mu_1 = \mu_2$	Respondents to first mailing	46	0	0.85	-0.40358	0.6877	No
		Respondents to second mailing	33	1	1.06			

Significant differences in the median ordinal values for regional location (state) between early respondents and late respondents were not detected at the $\alpha = 0.05$ level ($z = 1.459$, $p = .1446$). However, significant differences were detected in the median company corporate structure ordinal value of early respondents and that of late respondents ($z = 2.118$, $p = .0342$). To double check the test, the Kruskall-Wallis test was conducted to see if the two samples were representative of the same population. The Kruskall-Wallis H statistic was calculated and assumed to be distributed as χ^2. The null hypothesis of identical populations was rejected at the $\alpha = 0.05$ level ($H = 4.4849$ with 1 degree of freedom, $p = 0.0342$). A series of tests on the similarity of proportions was conducted. It was determined that the earlier respondents were more likely than late respondents to be single companies with single plants and that late respondents were more likely than early respondents to be multi-plant/multi-company corporations. However, it was noted earlier that firms that were willing to participate in telephone interviews tended to be structured as corporations. When the telephone interviewed companies were removed from the sample of late respondents, the Mann-Whitney U-test did not detect significant differences in the median ordinal values of corporate structure, indicating a lack of non-response bias. Therefore, the inclusion of the telephone interviews in the sample may bias the results slightly towards the perceptions of corporations.

4.2.7 Missing values

Many of the questionnaires that were returned had at least one question that the respondent did not answer. When considering each set of responses for a particular technology to be a data set, nearly two-thirds of the data sets for which adoption resistance scores could be calculated had at least one unanswered question. There are four possible options for handling missing values: 1) substitute neutral values for the missing values, 2) substitute an imputed response for the missing values, 3) delete respondents with any missing responses from the study, or 4) use only the respondents with complete responses for each calculation (Malhotra 1993). Given the nature of the multinomial logit model, options 3 and 4 would be the same and the number of data points would be greatly diminished if one of these options was employed in this study. The use of imputed responses (option 2) could introduce large amounts of bias. The use of neutral values (option 1) appeared to be the most logical; it was reasonable that if the reason for someone nat answering a question was because they did not know the firm's perception of a particular risk factor, then the firm probably did not have very strong opinions with respect to that factor. Neutral values were assumed more often toward the end of the survey. This may be due to the fact that some respondents may have run out of time or may have reached their survey tolerance level.

If a respondent did not provide enough information to determine an adoption resistance score for a particular technology, then that particular case was eliminated from the study. Also, if a respondent did not provide responses to questions concerning firm size (number of employees), technical expertise (number of engineers), or technical progressiveness.2 (number of trade shows attended in the past year), they were eliminated from the study. In these last three instances, the most logical neutral value would have been the mean, but given the effect of the outliers on the means (as discussed in chapter four), use of the means as substitutes for missing values did not seem reasonable.

4.3 Profile of respondents

4.3.1 State

Four of the five states of interest were well represented by the respondents to the survey (Figure 4.1). Of the 46 wood furniture firms targeted in Louisiana, responses were received from only two firms. Reports from the Louisiana Forest Products Laboratory indicate that the industry within that state is characterized by a large number of small firms with relatively low technological levels (Vlosky and Harding 1995, Vlosky and Chance 1995, Vlosky 1996). Therefore, it was assumed that the arbitrary nature of the state boundaries would have little effect on the applicability of the survey results to firms in Louisiana. Firms in Louisiana have been surveyed extensively in recent months (Smith 1997), so the reason for the low response rate might be that Louisiana firms have reached their survey saturation level.

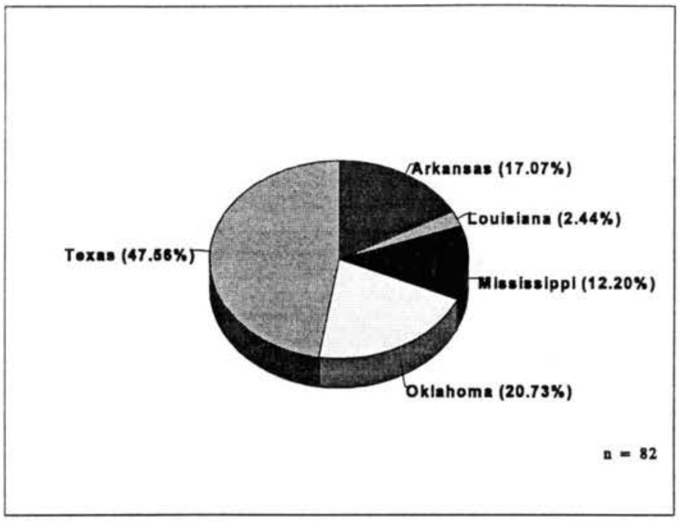

Figure 4.1. Geographic distribution of respondents

A higher than expected response rate was achieved from the state of Oklahoma (20.7% achieved vs 8.3% expected). Since the survey was mailed through Oklahoma State University, state/school loyalty appears to have influenced the response rate from Oklahoma.

4.3.2 Firm size

Based on survey responses, it appears that the wood products industry in the South Central US is characterized by a large number of small firms with a few very large firms in the population (Figure 4.2). The average number of employees for the entire set of respondents was 100 employees. However, this figure included the two outlying firms with more than 1000 employees. Once the outliers had been removed, the mean number of employees for the reduced respondent pool was 44 employees. The median number of employees was 9.25, the mode was 2 and the range was 3099.

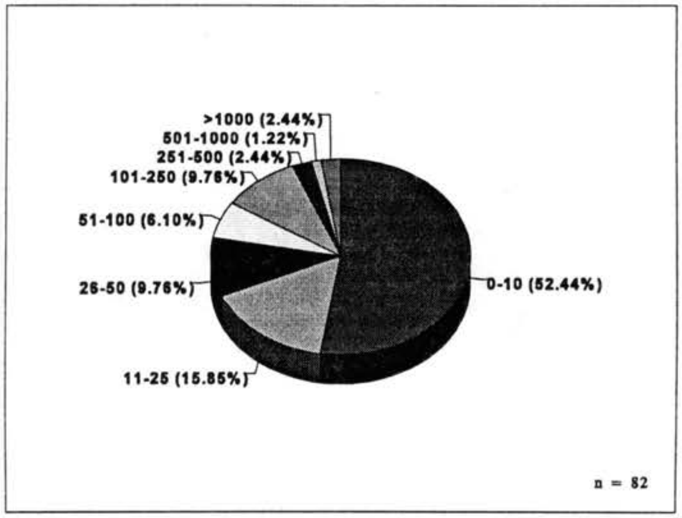

Figure 4.2. Firm size of respondents as measured by number of employees.

4.3.3 Corporate structure

The wood furniture industry in the South Central United States appears to be characterized by a large number of firms structured as single companies with only one plant each. The majority of the firms responding to the survey (55 out of 82 or 67%) were structured as a single company with a single plant (Figure 4.3). Fifteen respondents indicated that they were part of a corporation while 11 other respondents indicated that they were part of a single company that had multiple plants. Similarly, 71% of respondents to West's 1990 survey of wood household furniture manufacturers across the entire country represented firms structured as single plant/single company.

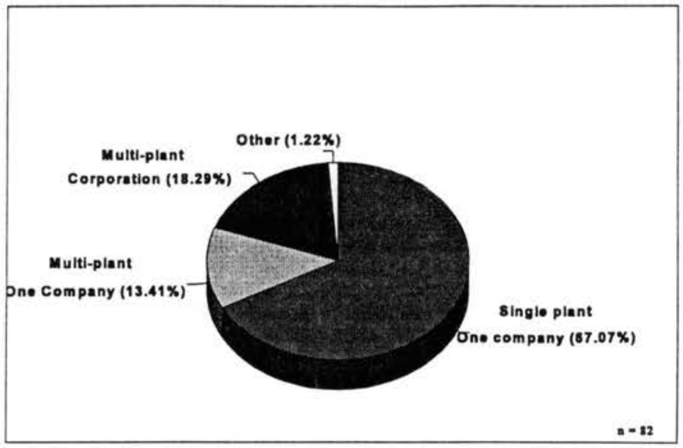

Figure 4.3. Corporate structure of respondents.

4.3.4 Firm age

Firms responding to the survey have been in business an average of 20.3 years. The median firm age was 15 years. Nearly 73% of the responding firms had been in business for no more than 20 years (Figure 4.4). It was noted earlier that many of the firms surveyed had ten or fewer employees. Unless otherwise forced out of business, these small firms may stay in business only as long as the primary decision maker (in this case, usually the owner/founder) *wants* to stay in business. Also, the high number of undeliverables and out-of business firms in the sample frame indicates that there may be high turnover in the industry. It would be likely that firms would be forced out of business during their "early days" when capital resources may not be as available, and business experience may be minimal.

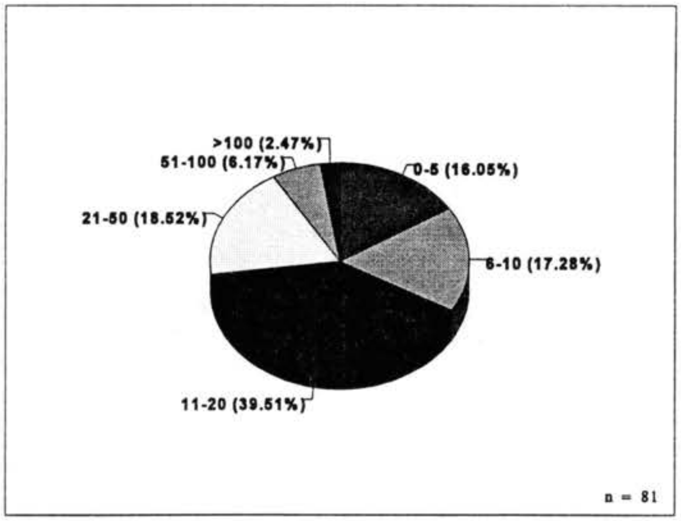

Figure 4.4. Number of years in business of survey respondents

4.3.5 Number of engineers employed

Technical expertise as measured by the number of engineers employed does not appear to be prevalent among wood products firms in the South Central US. Over 67% of the 79 firms responding to this survey question do not employ any engineers (Figure 4.5). The average number of engineers employed by responding firms was 1.6 with a sample standard deviation of 6.0. The median number of engineers employed was zero engineers and the mode was zero engineers.

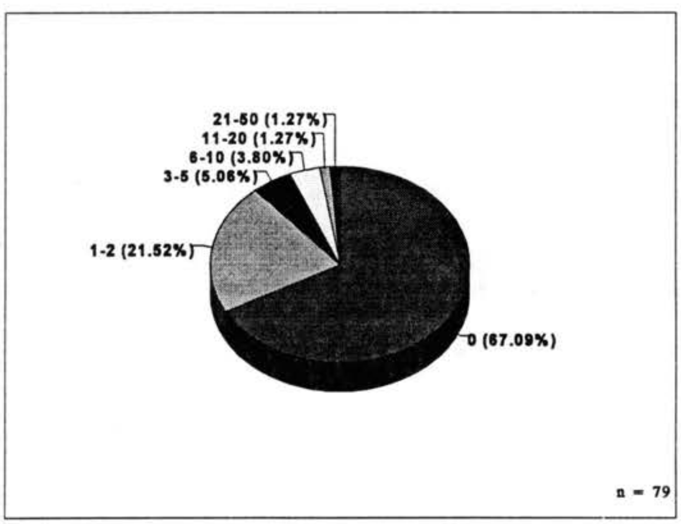

Figure 4.5. Number of engineers employed by responding firms

4.3.6 Products produced

Wood household furniture manufacturers were the largest segment of the wood products industry represented in the survey responses (Figure 4.6). Wood cabinets and wood store fixtures and furnishings were the second most popular products produced by the survey respondents. Nearly all the respondents indicated that they primarily produce finished goods with a few firms indicating that they manufacture intermediate parts as their primary product for sale (Figure 4.7).

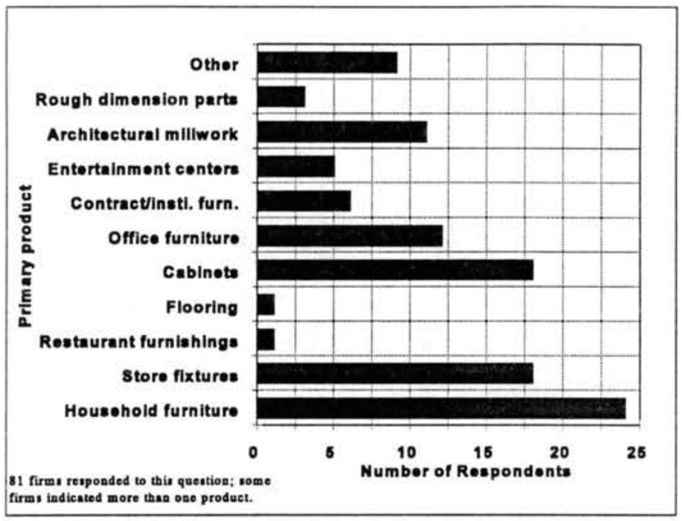

Figure 4.6. Products produced by survey respondents.

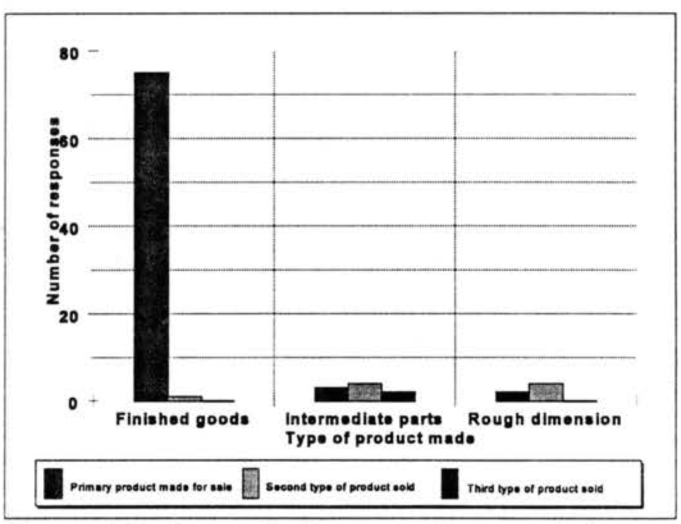

Figure 4.7. Form of primary products made for sale by survey respondents.

Chapter 5. Analysis

5.1 Overview

The hypotheses (discussed in chapter three, sections 3.1 and 3.2) and research objectives (discussed in chapter one) require the comparison of adopters and rejecters. The research question is: Can we predict whether or not a firm with certain characteristics and perceptions of risk factors is likely to be an adopter or a rejector of certain technologies? Or more precisely, can we predict the adoption resistance of a firm with respect to certain technologies given the firm's characteristics and perceptions of risk factors?

As discussed in chapter three, three different levels of analysis were conducted to investigate these questions. The first level discussed in this chapter consisted of an analysis involving all six technologies grouped together. The second level of analysis focused on technologies grouped by their "hardness". This involves discussion on two data sets: data related to hard technologies (thin saw kerf technology, CNC machining, and water-based finishes) and data related to soft technologies (self-managed/cross-functional work teams, statistical process control, and pc-based production control). The final level of analysis focused on technology-specific data. The technology-specific discussion involves six data sets. These discussions are preceded by a review of the model, and the factors involved in the model.

5.2 Multinomial logit model

The multinomial logit model is often used when the dependent variable is categorical in nature (e.g., Baker 1992, Gatignon and Robertson 1989). In this research, categories reflect adoption/rejection behavior. "Some level of information relevant to the adoption decision is lost by grouping all nonadopters as a single category" (Gatignon and Robertson 1989). Therefore, a continuum of adoption resistance was approximated by five decision states as discussed in chapter three[21]. These five decision states or outcomes reflect different amounts of adoption resistance, and thus, are called adoption resistance levels (ARLs).

[21]Discussion found mainly on pages 72 and 88.

The relationship between these levels of adoption resistance and the technology adoption continuum are shown in Figure 5.1. To analyze the extent to which the variables discussed in chapter three predict the category or the adoption resistance level of an organization, the multinomial extension of the binomial choice model (multinomial logit) was used.

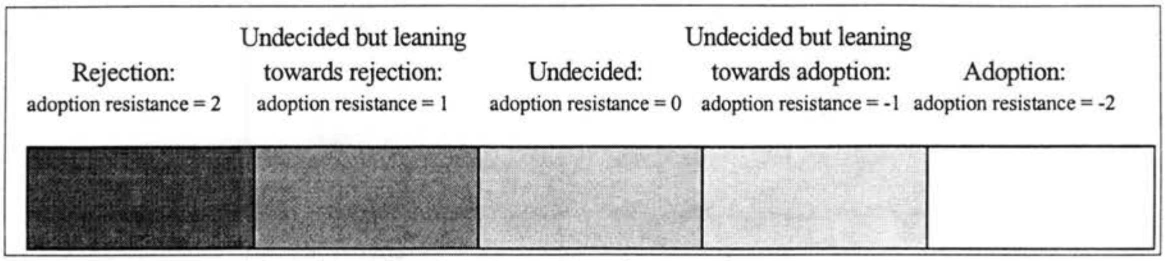

Figure 5.1 Approximation of technology adoption continuum.

One could estimate the effects of each of the variables on the log odds of each pair of outcomes, or the effects of each variable on the odds of each outcome against the other four outcomes pooled. Since the equations of each approach are not truly independent (the same data are used in more than one equation), the estimated standard errors and inferential statistics may be too optimistic. Also, there is no guarantee that the estimated probabilities of the outcomes will sum to unity if the equations are estimated independently (Hanneman 1997). The multinomial logit model estimates the log odds of any four of the five outcomes, and derives the effects with regard to the fifth by solving the log odds equations simultaneously.

Let D_i be the adoption resistance level of organization i. $\mathbf{X}_i$ will be the vector of variables for organization i and $\mathbf{X}_i'$ is the transpose of the $\mathbf{X}_i$ vector. The multinomial choice model can be expressed as:

$$P_{ij} = P(D_i = j|X_i) = \frac{e^{(\beta_{0j} + X_i'B_j)}}{\sum_{k=-2}^{2} e^{(\beta_{0k} + X_i'B_k)}}.$$

where P_{ij} = probability that organization i belongs to category j where $j \in \{-2, -1, 0, 1, 2\}$ with the values -2 through 2 representing the adoption resistance level, β_{0j} represents the intercept, and B_j = vector of coefficients $([\beta_{1j}, \beta_{2j}, \ldots, \beta_{14j}]')$

representing the marginal utilities of each of the n independent variables for resistance level j.[22] The β coefficients are estimated by maximizing the log likelihood function, using the Newton-Raphson iterative method (McFadden 1974, SAS Institute Inc. 1989).

The vector $\mathbf{X}_i$ will be comprised as:

x_{i1} = technical progressiveness.1,
x_{i2} = technical progressiveness.2,
x_{i3} = past experience,
x_{i4} = firm size,
x_{i5} = technical expertise,
x_{i6} = firm's perception of incommunicability,
x_{i7} = firm's perception of non-trialability,
x_{i8} = firm's perception of discontinuity,
x_{i9} = firm's perception of incompatibility,
x_{i10} = firm's perception of irreversibility,
x_{i11} = firm's perception of time to implementation,
x_{i12} = firm's perception of time to realization,
x_{i13} = firm's perception of difficulty of modification, and
x_{i14} = firm's perception of indivisibility.

The multinomial logit results are interpreted relative to one of the outcomes. In this research, the analysis was conducted five times: once with each level of adoption resistance as the benchmark value.

A graph showing the relationship between the levels of a particular factor with the probabilities of each adoption resistance level (ARL) is helpful in interpreting the results. If a factor is determined to be positively related to technology adoption resistance, then the graph would have similar characteristics (i.e. the probability curves would have similar shapes) to the one shown in Figure 5.2. As the probability of a level decreases, the probability of the next higher level increases until the probability of the level after that forces the preceding level to decrease. The probability of an ARL of -2 starts high and approaches zero as the factor level increases. The probability of an ARL of -1 does not start quite as high as that of an ARL of -2; however, it is still higher than the starting points of probabilities of ARLs of 0, 1, or 2. Also, this

[22] For a more detailed discussion of the development of the multinomial logit model, the reader is referred to McFadden (1974). To confirm this representation and application of the model, the reader is referred to Gatignon and Robertson (1989) or to the Internet site of http://wizard.ucr.edu/~rhannema/glm/mlogit.htm where Dr. Robert Hanneman of the Department of Sociology at the University of California, Riverside has an excellent discussion of the multinomial logit model, how to use SAS to perform this modeling function, and how to interpret the SAS output.

probability increases slightly as the probability of an ARL of -2 decreases; then it begins to decrease as the probability of an ARL of 0 increases. This same pattern repeats itself after a slight lag as the level of the factor increases.

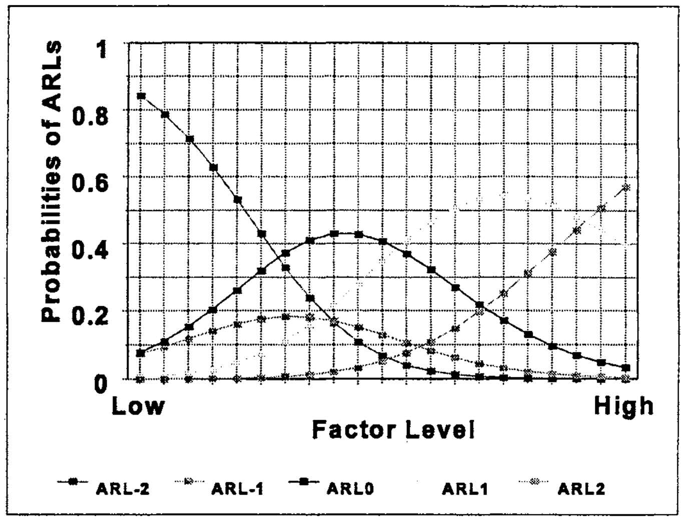

Figure 5.2. Expected shapes of probability curves for each ARL when increased level of factor is associated with increased adoption resistance.

The sums of the probabilities are shown to add to one for any given level of the factor in Figure 5.3. Figure 5.3 provides the same information as Figure 5.2; it is simply presented in a slightly different way. Since the sums of the five probabilities must equal one, this graph emphasizes what portion of the sum of probabilities represents the specific probability of each ARL. These stacked probability graphs will always have a range of zero to one. The line graphs, or their bar graph counterparts, will have a variable range dependent on the maximum of the probabilities associated with any of the ARLs. These types of graphs will be used throughout this chapter.

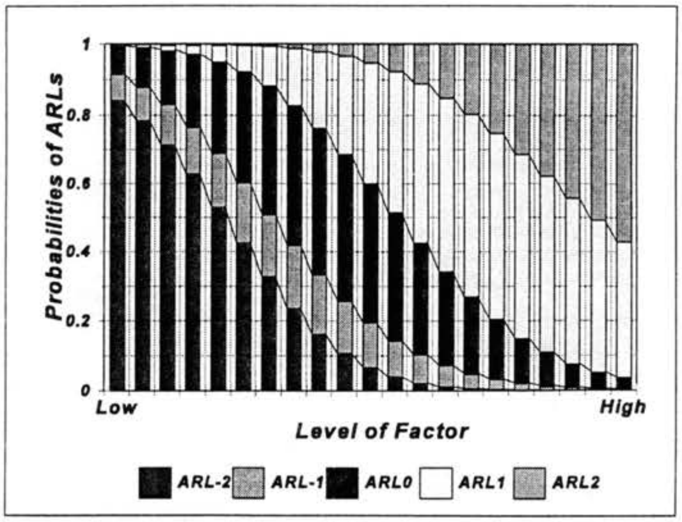

Figure 5.3. An example of expected changes in probabilities if an increased level of a factor is associated with increased adoption resistance.

5.2.1 Adoption resistance score

The adoption resistance score is the dependent variable in the multinomial logit model. Respondents to the questionnaire (profiled in chapter four) were asked to indicate awareness of and interest in each technology using two questions. Using word descriptions of the various responses, the first question asked respondents to indicate awareness/interest level to attain an awareness/consideration sub-score. These responses were coded as shown in Table 5.1.

Table 5.1. Codes for the responses to awareness/consideration sub-score

Question wording	Code for response
Not aware of technology	-3
Acquired and already disposed of technology	-2
Rejected the idea of using this technology after considering it	-2
Considering, but leaning towards rejecting	-1
Considering (no strong feelings towards rejecting or acquiring)	0
Aware of but not considering using	0
Considering, but leaning towards acquiring	1
Acquired and implemented	2

A decision was necessary regarding how to code responses that indicated the firm had acquired the technology in question, but had already disposed of it. Did this constitute adoption or rejection? During the pre-testing of the questionnaire, it became apparent that the people who had acquired a certain technology based their answers on what their actual experience had been rather than what they had expected prior to acquisition. Therefore, those responses were considered rejections.

The response "Aware of but not considering using" was meant to capture firms which were aware of a certain technology, but who had not given serious consideration to the possibility of acquiring that technology. It seemed most appropriate to consider this as a neutral response because it did not reflect any particular tendencies towards either adoption or rejection.

The second question asked respondents to indicate their level of interest in adopting or rejecting each technology using a 0 to 10 point likert-type scale with 0 = Reject and 10 = Adopt. Since it was presumed that respondents who indicated a value very close to the extremes of adoption or rejection would likely "end up" at the extremes, these responses were transformed into a 5 point scale (0-1 = -2, 2-3 = -1, 4-6 = 0, 7-8 = 1, 9-10 = 2) to generate an interest sub-score. This is consistent with methods in the literature (e.g. Gatignon and Robertson 1989). If a respondent answered both questions, the two sub-scores were averaged and rounded to the next integer of greater or equal magnitude to comprise an adoption/rejection score. If the respondent indicated no awareness, but gave an interest sub-score, the interest sub-score was ignored and treated as an unanswered question since interest is conditional on awareness. If the respondent indicated an awareness of the technology, but did not respond to the interest sub-score scale, then the awareness/consideration sub-score was considered an estimate of the adoption/rejection score. Since the score is used to reflect adoption resistance, scores of -2, -1, 0, 1, and 2 were pivoted about the value of zero to obtain the adoption resistance score. Examples of raw data and the resulting adoption resistance scores are given in Table 5.2.

Table 5.2. Examples of calculation of adoption resistance score

	Respondent					
Score Segment	R1	R2	R3	R4	R5	R6
Awareness/consideration sub-score	0	blank	-3	0	-3	1
Level of Interest (Raw)	5	blank	0	1	blank	6
Interest sub-score	0	.*	.*	-2	.*	0
Adoption/rejection score	0	.*	-3	-1	-3	1
Adoption resistance score	0	.*	-3	1	-3	-1

* A period indicates a blank response (missing value).

5.2.2. Measures

The measures for the study are reported in Table 5.3. Since several of the variables were assessed by using multi-item measures, alpha coefficients (Chronbach's alpha) were determined using the CORR procedure in SAS (SAS Institute Inc. 1990). Chronbach's alpha is an internal consistency measure that provides an indication of whether or not individual items in multi-item measures are summative. In most cases, the alpha coefficient was determined to be reasonable. However, incompatibility, irreversibility, and technical progressiveness measures have less than satisfactory alpha coefficients (< 0.60).

In the case of incompatibility, further investigation revealed that the primary reason in reducing the value of the alpha coefficient was the set of responses regarding water-based finishes. While the measure was retained within the study, its inclusion may have an effect toward insignificance of the incompatibility variable, especially in the case of the water-based finishes. The extremely low value of the coefficient alphas associated with the irreversibility and technical progressiveness measures indicate that assuming the proposed measures to be summative may not be reasonable. Again, it should be noted that inclusion of these variables as summative measures may contribute to their testing insignificant during the analysis.

Since the maximum likelihood estimators for the β coefficients may approach infinity if there is substantial collinearity among the variables, Pearson's correlations were calculated for each pair of the fourteen variables. The correlation matrix is presented in Table 5.4. The Pearson correlation coefficients ranged in magnitude from 0.00 to 0.19. Since correlation was generally low, collinearity was not believed to have a significant impact on the study.

Table 5.3. Summary of measures

Variable		Measure	Coefficient alpha
Incompatibility	3-item:	Q18: This technology fits easily into our production facility. (Strongly disagree - Strongly agree)*	0.50
		Q20: This technology would/did require a substantial amount of training before implementing in our plant. (Strongly disagree - Strongly agree)	
		Q21: Using this technology is/was supported by upper management. (Strongly disagree - Strongly agree)*	
Discontinuity	2-item :	Q23: When considering this technology, how would/did you characterize this technology? (Completely new to the firm - Modification or extension of current technology) **	n.a.
		Q24: When considering this technology, do/did you consider this a major change in the production process or a minor change in the production process? **	
Non-trialability	3-item:	Q22. There is/was sufficient opportunity to see the operation/application of this technology prior to purchasing/applying it. (Strongly disagree - Strongly agree)*	.69
		Q26: How easy is it to test this technology using simulation or off-line trials prior to adopting it? (Very difficult - Very easy)*	
		Q27: This technology can be implemented and run in parallel with current technologies. (Strongly disagree - Strongly agree)*	
Indivisibility	1-item:	Q25: How easy is it to adopt this technology in stages? (Very difficult - Very easy)*	n.a.
Incommunicability	3-item:	Q28: Do you agree that information regarding the benefits of this technology is readily available? (Strongly disagree - Strongly agree)*	.61
		Q29: How difficult is it for your firm to obtain information regarding this technology? (Very difficult - Very easy)*	
		Q30: What are the main benefits you would expect if you acquired this technology? (Reduced costs, improved quality, improved communication)	
Time to implementation	1-item	Q31: Suppose that today, you made the decision to obtain this technology for your plant. When do you think it would be fully implemented? (Within a month - More than a year)	n.a.

Variable		Measure	Coefficient alpha
Realization	1-item :	Q32: Suppose you were to begin implementing this technology today, when would you expect to start seeing the expected benefits? (Within a month - More than a year)	n.a.
Difficulty of modification	1-item :	Q19: This technology could be easily modified to work with our production system. (Strongly disagree - Strongly agree)*	n.a.
Irreversibility	2-item:	Q33: How would you characterize the lost time, money and effort spent on this technology should it prove to be ineffective for your plant? (Very significant - Very insignificant)	.26
		Q34: Do you agree that this technology would be difficult to abandon if it proves ineffective? (Strongly disagree - Strongly agree)	
Technical progressiveness.1	2-item:	Q11: Our company believes it is important to develop expertise on existing production technologies. (Strongly disagree - Strongly agree)	.36
		Q12: Our firm is willing to make plant space available for experimentation with new equipment. (Strongly disagree - Strongly agree)	
Technical progressiveness.2	1-item:	Q13: In the past year, how many trade shows has a representative from your firm attended? (Count)	n.a.
Past experiences	1-item:	Q14: In general, how would you describe your firm's past experiences with new technology? (Very disappointed - Very pleased)	n.a.
Firm size	1-item :	Q4: Number of full-time employees (all) + ½ * Number of part-time employees (all)	n.a.
Technical expertise	1-item :	Q6: How many engineers does your firm employ? (Count)	n.a.

* Responses must be pivoted about the neutral response. ** Responses combined as described in Section 3.3.1.2.

Table 5.4. Correlation matrix of variables

	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}	x_{13}	x_{14}
x_1 (tech prog.1)	.0347	.1372	-.0212	-.1636	.0339	-.0587	.0085	.0836	-.0468	.0338	-.1160	-.0069	.0377
x_2 (tech prog.2)	1	.1067	.1209	.0566	-.0873	-.0147	-.0925	.0173	.0788	-.05447	-.0666	.0088	.0140
x_3 (past exper.)		1	.0878	.0908	.0885	-.1910	-.1417	-.1233	.0543	.0007	-.0442	-.0742	-.0420
x_4 (firm size)			1	-.0352	.0493	.0526	-.1790	-.0521	-.0856	-.0748	.0497	.0717	.0095
x_5 (tech expert.)				1	.0041	.0303	.0681	-.1135	-.0119	-.0842	.0487	-.1198	-.1096
x_6 (incommu.)					1	-.0161	.0983	.1256	-.1395	.0003	-.0678	.0099	.1071
x_7 (non-trial.)						1	-.0230	.1113	.0636	-.0931	.0087	.0539	-.0777
x_8 (discont.)							1	.0323	.0782	.0309	-.0849	-.0083	-.0983
x_9 (incompat.)								1	-.0333	.0996	.0236	.1550	.0205
x_{10} (irrevers.)									1	-.0373	.1521	.1129	-.0698
x_{11} (time to impl.)										1	.0085	-.1044	.0454
x_{12} (time to real.)											1	.0639	.1176
x_{13} (diff. of mod.)												1	.0921
x_{14} (indivis.)													1

5.3 Overview of analysis presentation

Since the same type of analysis was conducted on different sets and subsets of the data, an outline of the way the data is presented and clarification of terms may be warranted. First of all, response outcome categories refers to the five levels of adoption resistance. The data were analyzed at three different levels. The level of analysis refers to the grouping of the data. There are three different levels in this study: all technologies, technologies grouped by hardness, and individual technologies. The analysis associated with each level is presented in its entirety. The data set for each level refers to the set of survey responses associated with that level. At the beginning of each new analysis, the data set is briefly described with respect to the types of technologies involved in the data set, and the frequency of observed levels of adoption resistance. Level 1 analysis concerns all technologies, so there is one data set associated with that level. Level 2 analysis concerns technologies grouped by hardness; two data sets are associated with that level. Level 3 analysis concerns individual technologies, so six data sets are associated with level 3.

For each data set, the multinomial logit analysis is run with one adoption resistance level as a benchmark, and factors significantly affecting the probability of that benchmark level in relation to each of the other four levels are revealed. Each run of the multinomial logit analysis is called a case. Since there are five adoption resistance levels, the analysis is run five times for each data set, and thus there are five cases for each data set. These significant effects are used to determine support for the hypotheses outlined in chapter three (e.g., Feder and Slade 1984, Baker 1992, Gatignon and Robertson 1989). The analysis of variance reveals factors that have significant effects in explaining variance in adoption resistance levels, i.e., differentiating between levels of adoption resistance, when considering all five levels of adoption resistance at once. For each analysis, results from the analysis of variance are presented in table format; significant effects of each case and how they do or do not support the associated hypotheses are discussed; a summary of the effects of the significant factors in the analysis of variance is presented; and finally, a discussion on goodness-of-fit of the model is given.

5.4 Level 1 - all technologies

This level of the analysis consisted of all six technologies (thin saw kerf, CNC machining, water-based finishes, self-managed/cross-functional work teams, statistical process control, and pc-based production control). The multinomial logit analysis is limited in its effectiveness when dealing with small samples (SAS Institute Inc. 1989). A general guideline is to take the number of response outcome categories (in this study, number of adoption resistance levels) less one and multiply by 20 to 30. This gives the number of observations needed for a meaningful analysis. Also, it is recommended that no more than 20 percent of the response outcomes have less than 5 observations. The total number of observations for this analysis was 316. Results of the survey (observed results) are given in Table 5.5, and sample size and distribution criteria are met.

Table 5.5. Observed levels of adoption resistance (all technologies).

Adoption resistance level (response)	Frequency of response
Adoption	72
Leaning towards adoption	42
Neutral	88
Leaning to rejection	89
Rejection	25
Total	316

As mentioned earlier, the multinomial logit analysis was conducted five times for each data set, using a different benchmarking adoption resistance level in each case[23]. In order to facilitate the interpretation of the results of each of these cases, the results of one case (benchmark = neutral position) are presented with substantial explanation; then, the aggregate results, encompassing the results of all five cases, are presented.

[23]To gain a complete understanding, it is actually only necessary to run the analysis one time for each of the response outcome categories minus one. In this study, the response outcome categories are the adoption resistance levels. Since each effect involves two adoption resistance levels, and the significance of an effect is the same regardless of which of the two levels is the benchmark level, all effects will be revealed.

5.4.1 All technologies, benchmarking on neutral

Results of the multinomial logit analysis using the neutral position (adoption resistance level of 0) as the benchmark are given in Table 5.6. The null hypothesis being tested was that all the variables are nonrelevant (i.e. Ho: $\beta_{ij} = 0 \ \forall \ \beta_{ij}$, $i = 0, ..., 14, j = -2, ..., 2$). The p-values were determined through calculation of a chi-squared statistic, however, many articles in the current literature perform a t-test on the coefficient ($t = (0 - \beta_{ij})/$ standard error). Significance as reflected by p-values was very similar for the two statistics. These p-values reflect significance as it pertains to two levels of adoption resistance only; it does not necessarily reflect significance in explaining variance in the overall model.

Table 5.6. Logit analysis of factors affecting the probability of adoption resistance level when benchmarking on neutral (all technologies).

	Adoption (j = -2)		Lean to Adoption (j = -1)	
	estimate	p-value	estimate	p-value
Intercept (β_{0j})	6.0697	.1308	4.4037	.2800
β_{1j} Technical progressiveness.1	-.6504	.3432	.0657	.9205
β_{2j} Technical progressiveness.2	-.1497	.8670	.1434	.8752
β_{3j} Past experiences	1.0195	.1921	.2068	.7848
β_{4j} Firm size	-4.6990	.3721	-6.9337	.1974
β_{5j} Technical expertise	13.1955	.0283**	12.9702	.0331**
β_{6j} Incommunicability	-.4656	.5634	-.4308	.5704
β_{7j} Non-trialability	-.6569	.4082	-.5518	.4905
β_{8j} Discontinuity	-.5503	.0947***	-.4162	.2047
β_{9j} Incompatibility	-4.1829	.0002*	-1.1015	.2949
β_{10j} Irreversibility	.8423	.1401	.7786	.1825
β_{11j} Time to implement	-.3319	.5078	.8897	.0411**
β_{12j} Time to realization	-.0162	.9716	-.8044	.0488**
β_{13j} Difficulty of modification	-1.5056	.0127**	-1.4490	.0139**
β_{14j} Indivisibility	.6993	.2268	.8618	.1546

* indicates significance at the $\alpha = .01$ level
** indicates significance at the $\alpha = .05$ level
*** indicates significance at the $\alpha = .10$ level

Table 5.6. continued

	Lean to Rejection ($j = 1$)		Rejection ($j = 2$)	
	estimate	p-value	estimate	p-value
Intercept (β_{0j})	.1877	.9753	4.1407	.3333
β_{1j} Technical progressiveness.1	-.6824	.2104	-.2289	.7898
β_{2j} Technical progressiveness.2	-.3617	.7713	-.1286	.9394
β_{3j} Past experiences	-.5983	.3241	.5443	.5710
β_{4j} Firm size	-16.2513	.0219**	2.1819	.7737
β_{5j} Technical expertise	16.7094	.0070*	4.9957	.5568
β_{6j} Incommunicability	-.4343	.5348	-2.8022	.0081*
β_{7j} Non-trialability	-1.1945	.0930***	.1738	.8582
β_{8j} Discontinuity	-.2309	.4271	-1.1217	.0313**
β_{9j} Incompatibility	2.6316	.0017*	4.9231	.0001*
β_{10j} Irreversibility	.6679	.2017	1.4893	.0510***
β_{11j} Time to implement	-.2250	.5180	.6137	.2982
β_{12j} Time to realization	-.0725	.8309	-.0389	.9455
β_{13j} Difficulty of modification	.6417	.1637	.7204	.3639
β_{14j} Indivisibility	.6157	.2893	.6734	.4175

* indicates significance at the $\alpha = .01$ level
** indicates significance at the $\alpha = .05$ level
*** indicates significance at the $\alpha = .10$ level

Two variables appear to affect the probability of adoption resistance at three levels when compared to the probability of an ARL of 0. Number of engineers (x_5) and incompatibility (x_9) each show significant effects for three levels.

Technical expertise as measured by number of engineers appears to have a positive, significant effect on the log odds of an ARL of -2 (adoption) versus an ARL of 0 (neutral) ($p = .0283$). Likewise, it appears to have a positive, significant effect on the log odds of an ARL of -1 (lean to adoption) versus an ARL of 0 ($p = .0331$). So far, these results are what would be expected as outlined in Hypothesis 16 (the higher the technical expertise within a firm, the lower the adoption resistance). However, the coefficient for the ARL of 1 (lean to rejection) is also significant and positive (p = .0070). To understand these results, a graph of the impact that the number of engineers has on each level of technology resistance is employed. Holding all other variables at their means, probabilities were calculated at differing levels of the number of engineers, and those probabilities were plotted (Figure 5.4). The choice of a benchmarking level has no effect on these probabilities (i.e., these are absolute probabilities).

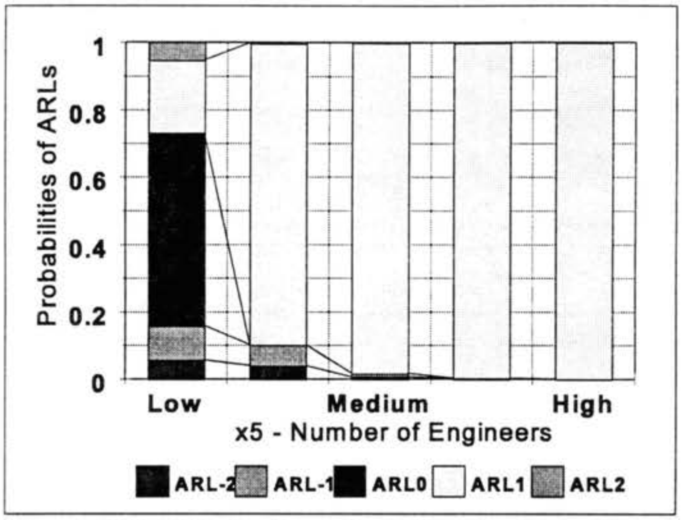

Figure 5.4. Effects of number of engineers on the probabilities of ARLs (all technologies).

It appears that an increase in the number of engineers results in a greater increase in the probability of an ARL of 1 than it does in an increase in the probabilities of ARLs -2 or -1. A plot of the adoption resistance levels directly affected by a change in the number of engineers (i.e. those levels for which number of engineers was significant when benchmarking on the neutral case) confirms this conclusion (Figure 5.5).

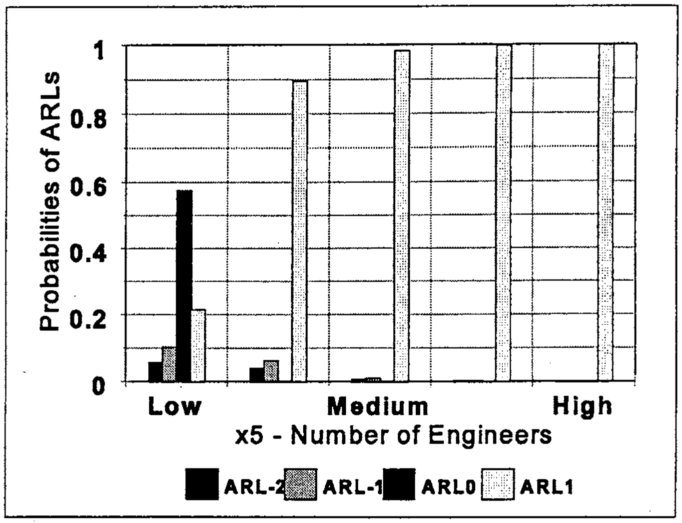

Figure 5.5. Significant effects of changes in the number of engineers on the probabilities of ARLs (all technologies, benchmarked on the neutral case).

A primary conclusion of this analysis of the effect of the number of engineers a firm employs is that as the number of engineers increases the likelihood of assuming a neutral position on a particular technology decreases (in this case, the probability of a 0 ARL approached zero very quickly). Even though the trends depicted in Figures 5.4 and 5.5 indicate little support for the initial indication of an increase in the number of engineers having positive, significant effects on the probabilities of ARLs of -1 and -2, it should be noted that these effects were determined to be significant when considering the change that occurs with respect to the change that occurs in the probability of the neutral option. If the rejection side of the continuum were ignored and the only possibilities considered were neutral, leaning to adoption and adoption, then as the number of engineers increased and the probability of a neutral position decreased, the probability of a lower adoption resistance level would necessarily increase. Therefore, there is some support for the hypothesis that lower technical expertise is associated with higher adoption resistance (Hypothesis 16).

Incompatibility also tests significant with respect to three levels of adoption resistance. The signs of the coefficients suggest that an increase in incompatibility would result in a decrease in the probability of an ARL of -2 and increases in the probabilities of ARLs of 1 or 2 each relative to the probability of an ARL of 0. Again, holding all other variables at their means, incompatibility was varied from low to high, and the resulting probabilities were plotted (Figure 5.6).

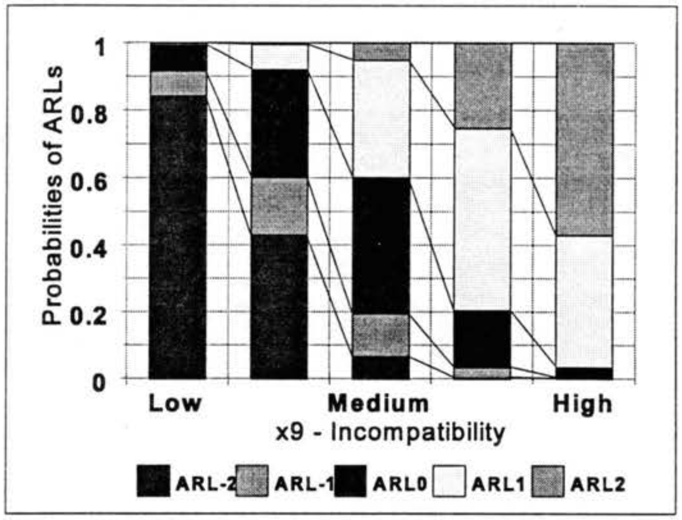

Figure 5.6. Effects of incompatibility on the probabilities of ARLs (all technologies).

By plotting these probabilities, it becomes apparent that higher incompatibility is associated with higher adoption resistance and Hypothesis 1 is strongly supported. The plot of the adoption resistance levels directly affected by a change in incompatibility also emphasizes this support (Figure 5.7).

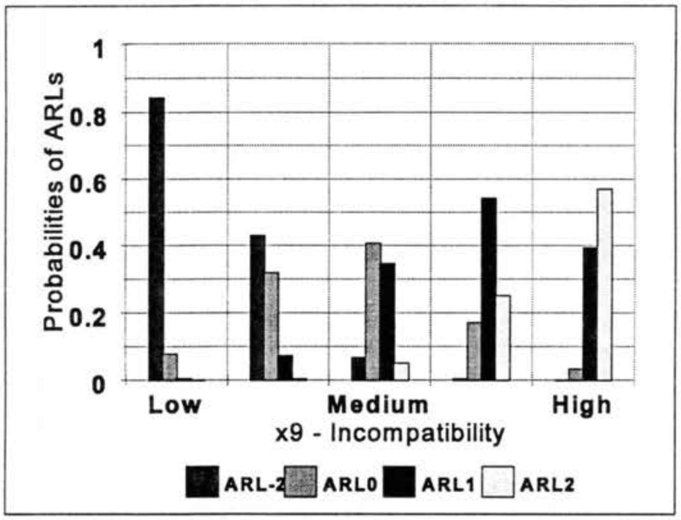

Figure 5.7. Significant effects of changes in incompatibility on the probabilities of ARLs (all technologies, benchmarked on the neutral case).

Discontinuity (x_8) tests significant with respect to ARLs of -2 and 2. In both instances, the coefficients have negative signs, implying that an increase in discontinuity decreases the log odds of an ARL of -2 versus an ARL of 0 ($p = .0947$) and it decreases the log odds of an ARL of 2 versus an ARL of 0 ($p = .0313$). The graph of the probabilities that result when holding all other variables at their means but varying discontinuity from low to high shows that as discontinuity increases, the probability of a neutral ARL increases and the probabilities of an ARL of 2 or an ARL of -2 do decrease (Figure 5.8).

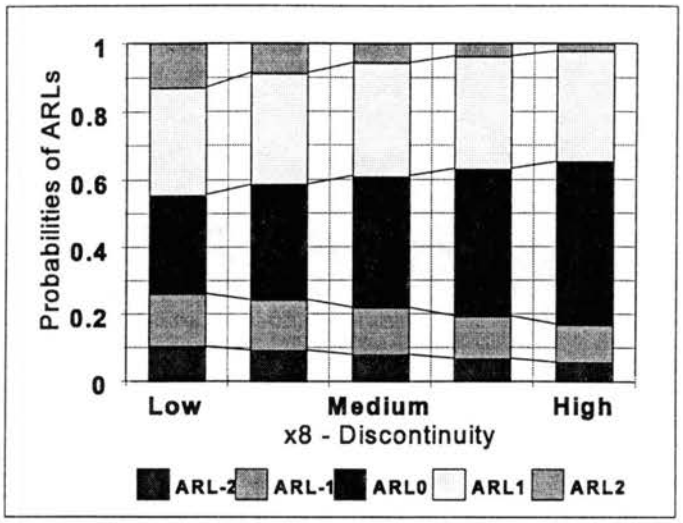

Figure 5.8. Effect of changes in discontinuity on the probabilities of ARLs (all technologies)

It appears that some support exists for the hypothesis that higher discontinuity is associated with higher adoption resistance (Hypothesis 2), up to the neutral level. Then, the trend appears to be in the opposite direction. Once again, this is confirmed when considering only those levels for which discontinuity appears to have a significant effect (Figure 5.9). There is insufficient evidence to support the hypothesis that higher discontinuity is associated with higher adoption resistance (Hypothesis 2) when considering the ARL of 1. However, given the negative coefficient of the effect when comparing ARL 2 with ARL 0 (p = .0313), there appears to be some evidence suggesting the opposite of Hypothesis 2.

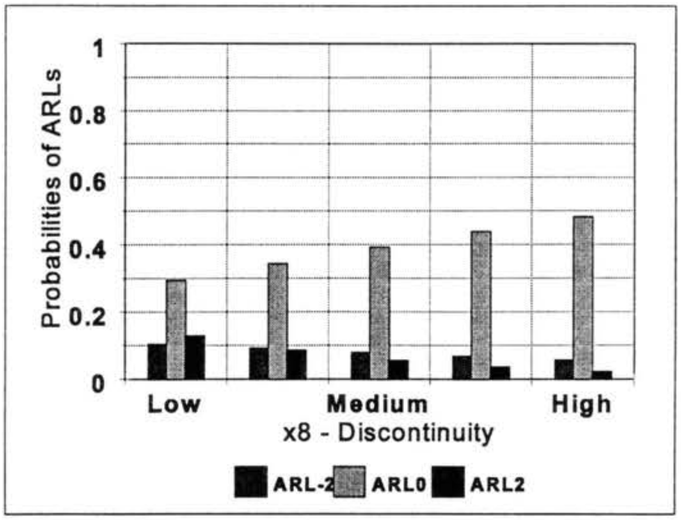

Figure 5.9. Significant effects of changes in discontinuity on the probabilities of ARLs (all technologies, benchmarked on the neutral case).

Difficulty of modification (x_{13}) tests significant at the two lower levels of adoption resistance. This suggests that difficulty of modification may help explain adoption behavior, but not necessarily rejection behavior. Figure 5.10 reflects the differences in probabilities effected by a change in discontinuity for all levels of adoption resistance while Figure 5.11 reflects differences only for those levels that test significant.

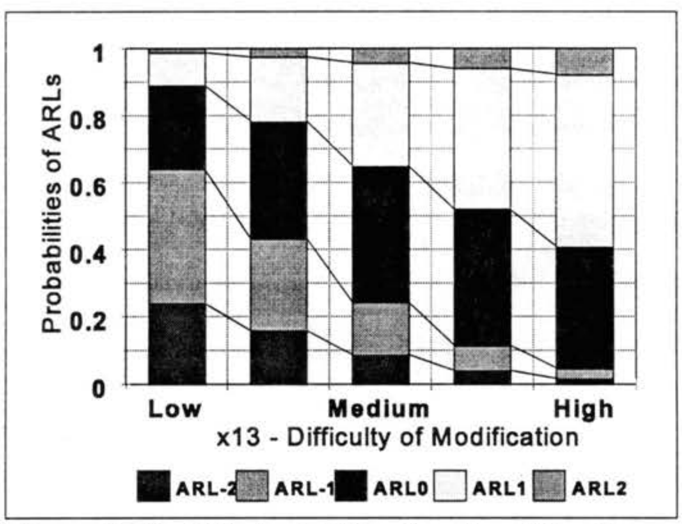

Figure 5.10. Effects of difficulty of modification on the probabilities of ARLs (all technologies).

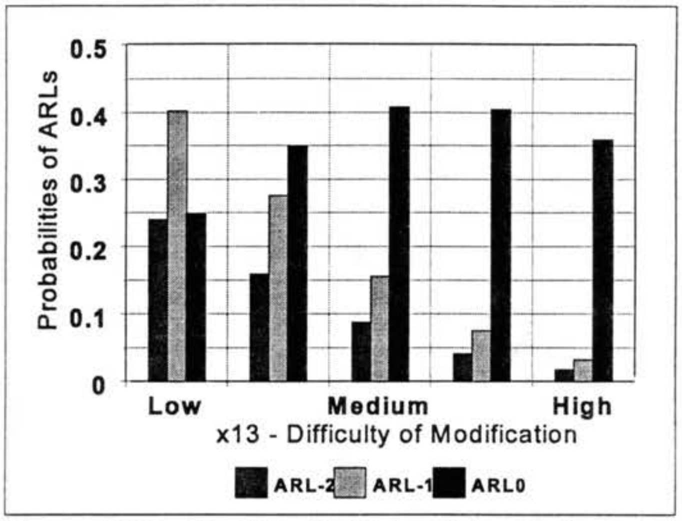

Figure 5.11. Significant effects of changes in difficulty of modification on the probabilities of ARLs (all technologies, benchmarked on the neutral case).

As can be seen in Figure 5.11, there is support for the hypothesis that higher difficulty of modification is associated with higher adoption resistance (Hypothesis 11) among the negative levels of adoption resistance. The positive coefficients for ARLs 1 and 2 suggest that this trend would continue through the positive ARLs, but at non-significant levels (visually suggested in Figure 5.10). Therefore, this empirical data suggest that difficulty of modification may help explain adoption behavior, but not necessarily rejection behavior. Also, while Hypothesis 11 is strongly supported at adoption levels, there is insufficient evidence to conclude any type of support for that hypothesis at the rejection levels ($\alpha = .10$).

The remaining variables that test significant have straight forward interpretations since significance is indicated at only one level for each variable. The negative coefficient on the x_4 variable (firm size) suggests that an increase in firm size would result in a decrease in the probability of leaning to rejection versus being neutral ($p = .0219$). The probabilities were again calculated and are shown in Figure 5.12.

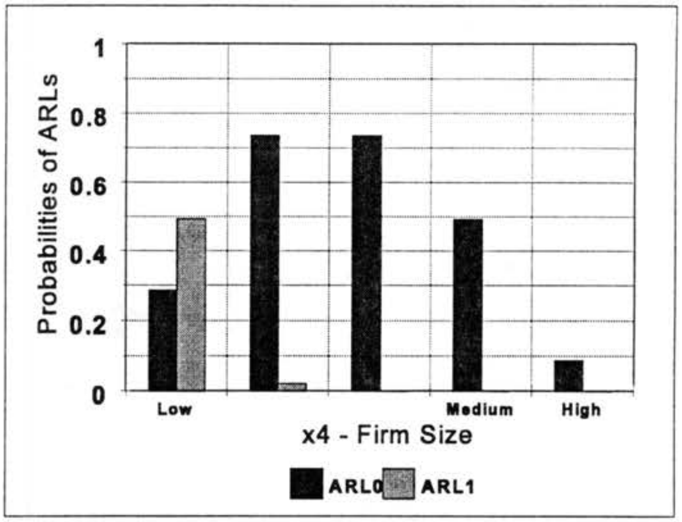

Figure 5.12. Significant effects of changes in firm size on the probabilities of ARLs (all technologies, benchmarked on the neutral case).

This suggests that smaller firm size would be associated with higher levels of adoption resistance. Therefore, this result suggests some level of support for Hypothesis 15 which infers that smaller firm size leads to higher adoption resistance.

Incommunicability has a significant effect with respect to the rejection level of adoption resistance (ARL 2). As incommunicability increases, the probability of an ARL of 2 decreases relative to the probability of an ARL of 0 ($p = .0081$). This is opposite from the relationship hypothesized (Hypothesis 7). Hypothesis 7 proposed that higher incommunicability is associated with higher adoption resistance.

Non-trialability has a negative, significant effect on the log odds of an ARL of 1 versus the log odds of an ARL of 0 ($p = .0947$) (Figure 5.13). This implies that to a minor extent, as non-trialability increases, adoption resistance decreases.

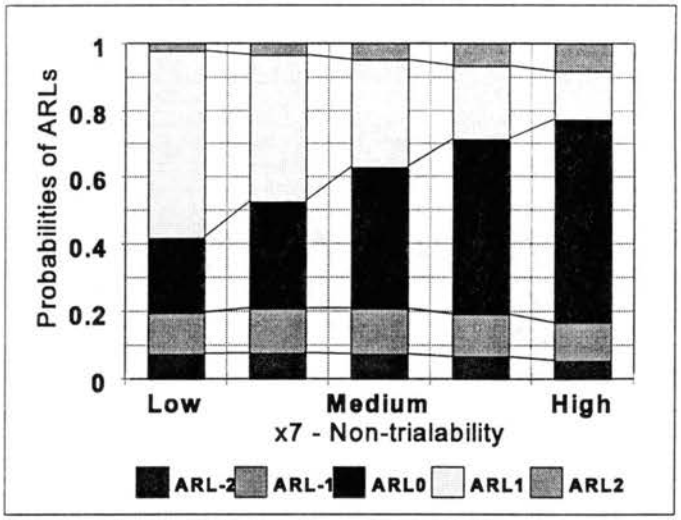

Figure 5.13. Effects of non-trialability on probabilities of ARLs (all technologies).

Irreversibility produces a positive, significant effect on the probability of an ARL of 2 vs an ARL of 0. This implies that as irreversibility increases, the probability of higher adoption resistance increases (Figure 5.14) and Hypothesis 11 (the higher the irreversibility of a technology, the higher the adoption resistance) is somewhat supported.

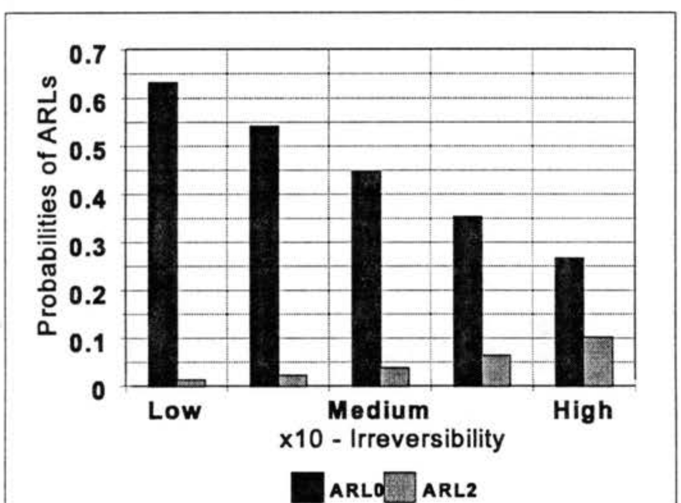

Figure 5.14. Significant effects of irreversibility on probabilities of ARLs (all technologies, benchmarked on the neutral case).

Time to implementation has a positive effect on the probability of an ARL of -1 versus an ARL of 0 (p = .0411). This suggests that as time to implementation increases, the likelihood of an ARL of -1 increases relative to the probability of an ARL of 0. This does not support the hypothesis that longer time to implementation increases adoption resistance (Hypothesis 8).

Time to realization has a negative effect on the probability of an ARL of -1 versus an ARL of 0 (p = .0488), suggesting that as time to realization increases, the probability of an ARL of -1 decreases and the probability of an ARL of 0 increases. This supports the hypothesis that longer realization time leads to higher adoption resistance (Hypothesis 9).

5.4.2. All technologies, all effects

To gain an understanding of all the effects that occur between each pair of adoption resistance levels, the same type of analysis as presented in section 5.4.1 must be conducted with each adoption resistance level as the benchmark. A discussion of all these effects is presented. However, the significance of these effects pertains to the probabilities of two adoption resistance levels at a time, and demonstrates possible support for the hypotheses outlined in chapter three. Significance as indicated by an analysis of variance is used to determine which of the characteristics and risk factors differentiate between the levels of adoption resistance. A summary of the analysis of variance is presented in Table 5.7.

As discussed earlier, five sets of effects are produced for each of the five cases conducted on each data set. The analysis of variance when considering all five levels of adoption resistance at once, is the same for each case conducted on a particular data set. The other four sets of effects are the β coefficients and reflect changes in probabilities of possible outcomes relative to the probability of the benchmark outcome. Since each of the five outcomes is used as the benchmark, the total number of relative effects generated is four times five = twenty. The effect of a variable on the probability of an outcome of Z versus an outcome of Y should be equal in magnitude but opposite in sign to the effect of that same variable on the probability of an outcome of Y versus an outcome of Z. This means that a maximum of ten relative effects are produced for a single variable. As long as all the β coefficients used are from the same case, the probability of a firm i with X characteristics having adoption resistance level j remains constant across all benchmarking levels. This will be called the absolute probability of adoption resistance level j for firm i.

Table 5.7. Analysis of variance (overall model, all technologies)

Source	p-value
Intercept	.3626
Technical progressiveness.1	.6148
Technical progressiveness.2	.9936
Past experiences	.3451
Firm size	.1273
Technical expertise	.0514***
Incommunicability	.1259
Non-trialability	.4116
Discontinuity	.1556
Incompatibility	.0000*
Irreversibility	.2811
Time to implementation	.0499**
Time to realization	.3141
Difficulty of modification	.0036*
Indivisibility	.6423

*Significant at $\alpha = .01$ level
**Significant at $\alpha = .05$ level
***Significant at $\alpha = .10$ level

The absolute probabilities of the adoption resistance levels do not change as the benchmarking level changes, but significant effects not affecting the original benchmark (the neutral case) become apparent. For this data set, a total of eleven factors have significant effects. Coefficients and p-values for each of these effects are given in Appendix F.

Past experience produces only one significant effect throughout the five cases. Past experience has a significant effect when using adoption as the benchmark adoption resistance level (p = .0573). The negative coefficient implies that as satisfaction with past experiences increases, the probability of an ARL of 1 (lean to rejection) decreases relative to the probability of an ARL of -2 (adoption). The changes in the probabilities are shown in Figure 5.15. Therefore, this provides some support for the hypothesis that less favorable past experiences with technology leads to higher adoption resistance (Hypothesis 13).

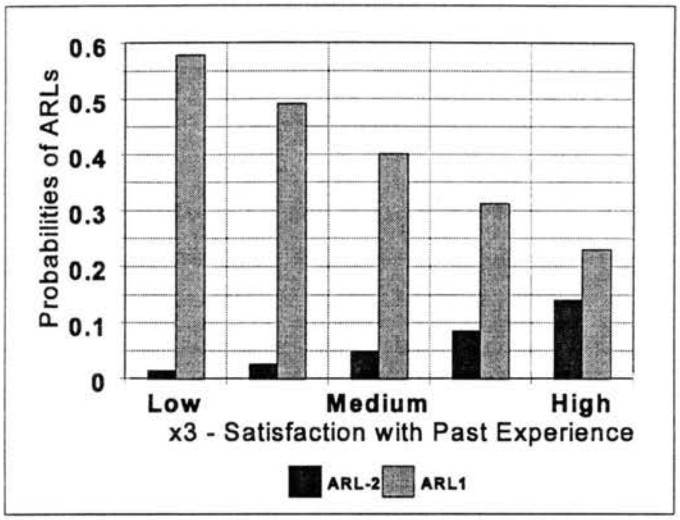

Figure 5.15. All technologies: significant effects of past experience on probabilities of ARLs (1 vs -2).

Firm size produces two significant relative effects. It is significant between ARLs 1 and 0 (p = .0219) and ARLs 1 and 2 (p = .0326). The coefficients indicate that as firm size increases, the probability of an ARL of 1 decreases relative to the probability of an ARL of 0; this is shown in Figure 5.16. This seems to support the hypothesis that smaller firm size is associated with higher adoption resistance (Hypothesis 15). The coefficients also indicate that as firm size increases, the probability of an ARL of 1 decreases relative to the probability of an ARL of 2. This is opposite from what was hypothesized. So, it appears that the support for the hypothesis is rather weak at best. The one conclusion that can be drawn is that based on this data, as firm size increases, the probability of an ARL of 1 decreases.

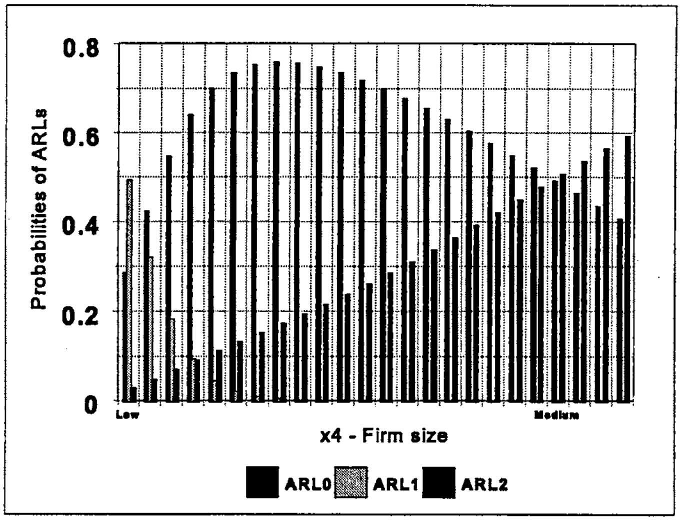

Figure 5.16. All technologies: significant effects of firm size on probabilities of ARLs (0 vs 2, 1 vs 2).

Higher technical expertise as measured by the number of engineers a firm employs was expected to increase the probabilities of lower adoption resistance levels (Hypothesis 16). This factor tests significant only when dealing with the neutral level of adoption resistance. Therefore, the earlier discussion on number of engineers summarizes the entire effect of technical expertise. The higher the technical expertise becomes, the lower the probability of a neutral position becomes (Figures 5.4 and 5.5). The coefficients indicate that as technical expertise increases, the probability of an ARL of -2 increases relative to the probability of an ARL of 0 ($p = .0283$); the probability of an ARL of -1 increases relative to the probability of an ARL of 0 ($p = .0331$). Both of these support Hypothesis 16. However, the probability of an ARL of 1 also increases relative to the log odd of an ARL of 0 ($p = .0070$). This does not support Hypothesis 16. Therefore, the support for the hypothesis is limited to the adoption side of the continuum. The three effects span four levels of adoption resistance indicating that technical expertise is likely to have some effect in differentiating among adoption resistance levels. The factor appears to be significant in the analysis of variance ($p = .0514$), providing statistical support for the suggestion that technical expertise appears to help differentiate between adopters and rejecters.

Incommunicability is significant whenever the multinomial logit model deals with a rejection level. In other words, incommunicability is significant at ARL -2 versus ARL 2 ($p = .0499$), ARL -1 versus ARL 2 ($p = .0377$), ARL 0 versus ARL 2 ($p = .0081$), and ARL 1 versus ARL 2 ($p = .0209$). As incommunicability increases, the probability of an ARL of -2 increases relative to the probability of an ARL of 2; the probability of an ARL of -1 increases relative to the probability of an ARL of 2. The trend continues with increasing incommunicability resulting in the probability of an ARL of 0 and the probability of an ARL of 1 increasing relative to the probability of an ARL of 2 (Figure 5.17). It was expected that higher incommunicability would be associated with higher adoption resistance (Hypothesis 7). Yet, none of these results show any support for Hypothesis 7. In fact, they show consistent and significant support for the opposite of Hypothesis 7. Since the effects span the continuum, it appears that, to a certain extent, incommunicability does differentiate between adoption resistance levels. However, lack of significance of this variable in the analysis of variance of all five resistance levels at once suggests that incommunicability's ability to explain variance is outweighed by the effects of incompatibility, difficulty of modification, time to implementation, and technical expertise.

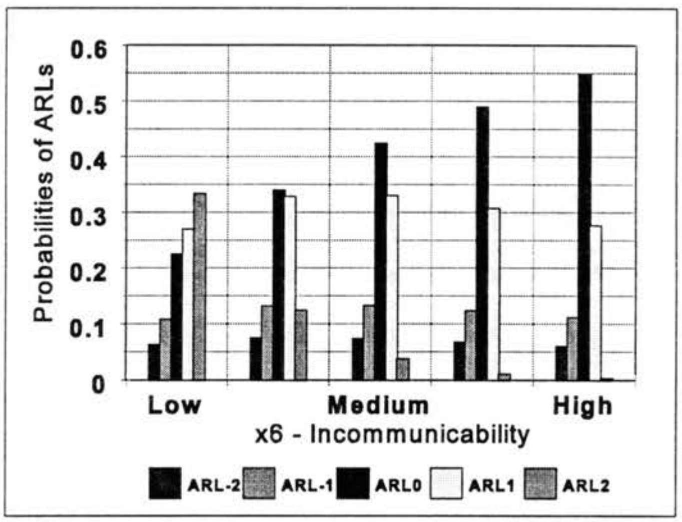

Figure 5.17. All technologies: significant effects of incommunicability on probabilities of ARLs (-2 vs 2, -1 vs 2, 0 vs 2, 1 vs 2).

Non-trialability did not have any significant effects other than the one discussed earlier (ARL 1 versus ARL 0, p = .0930). Just to summarize, the data suggest that there was no support for the hypothesis that higher non-trialability leads to increased adoption resistance (Hypothesis 3).

Discontinuity has negative, significant effects on the probability of an ARL of -2 and on the probability of an ARL of 2 relative to the probability of an ARL of 0 ($p = .0947$ and $p = .0313$, respectively). Discontinuity also has a negative, significant effect on the probability of an ARL of 2 versus the probability of an ARL of 1 ($p = .0742$). These effects are shown in Figure 5.18. It was hypothesized that greater discontinuity would lead to higher adoption resistance (Hypothesis 2). As can be seen in Figure 5.18, the effect between adoption and neutral (ARL -2 versus ARL 0) supports this hypothesis. However, the data does not support the hypothesis with respect to the other effects. The probability of an ARL of 2 decreases while the probability of an ARL of 0 increases as discontinuity increases. This is opposite from what was expected. Likewise, an unexpected effect occurs as an increase in discontinuity appears to increase the probability of an ARL of 1 relative to the probability of an ARL of 2. So, there appears to be minor support for Hypothesis 2 up to neutrality, and then the factor appears to have an opposite effect. Discontinuity appears to have significant relative effects that cover the continuum and specifically involve four of the five adoption resistance levels. Therefore, it appears that discontinuity has some ability to differentiate between adopters and rejecters although the effect is not monotonic across adoption resistance levels. This ability to differentiate appears to be minor when considering incompatibility, difficulty of modification, time to implementation, and technical expertise, since discontinuity does not appear to be significant in the five-level analysis of variance.

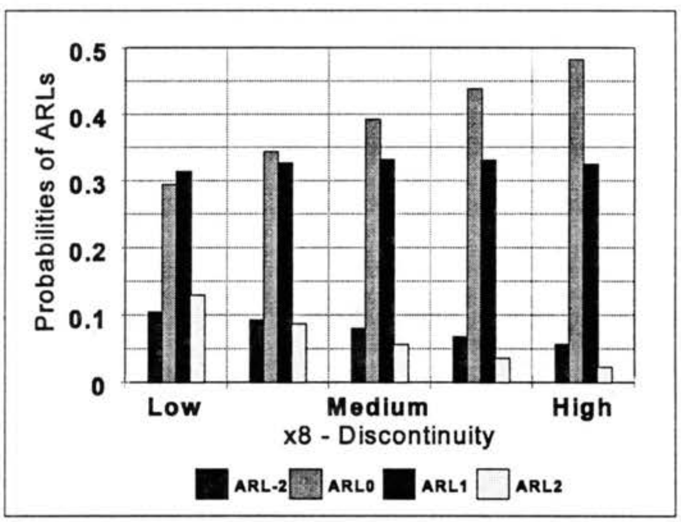

Figure 5.18. All technologies: significant effects of discontinuity on probabilities of ARLs (-2 vs 0, 2 vs 0, 2 vs 1).

The effects of incompatibility on the probabilities of all ARLs are shown in Figure 5.6. As stated before, this graph demonstrates vast support for the hypothesis that higher incompatibility is associated with higher adoption resistance (Hypothesis 1). When considering all the benchmarking levels, incompatibility has significant effects on nine pairs of levels of adoption resistance. All the effects support Hypothesis 1 and are shown in Figure 5.19. The effects span the continuum and incompatibility appears to differentiate between adopters and rejecters with a very significant effect in the analysis of the variance (p = .0000).

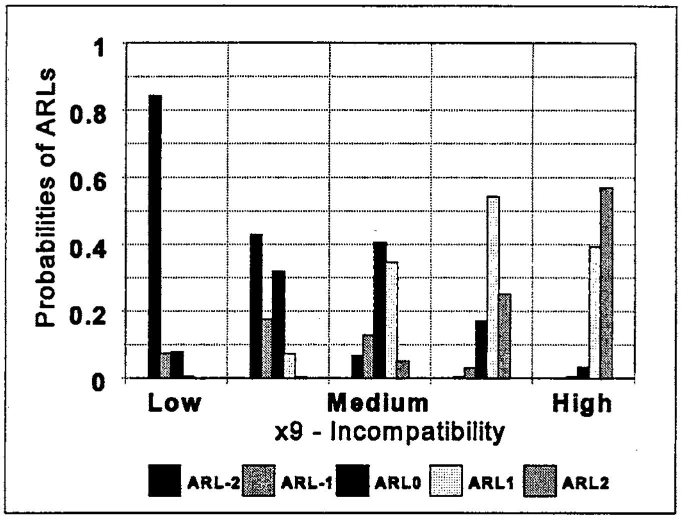

Figure 5.19. All technologies: significant effects of incompatibility on probabilities of ARLs (-2 vs 0, 1 vs 0, 2 vs 0, -1 vs -2, 1 vs -2, 2 vs -2, -1 vs 2, 1 vs 2, 1 vs -1).

Irreversibility produces significant effects between the probabilities of an ARL of 2 and an ARL of 0 only (p =.0510). This was discussed earlier with the conclusion being that the data provide some support for Hypothesis 11 (The higher the irreversibility, the higher the adoption resistance).

Time to implementation was expected to produce higher levels of adoption resistance as it increased (Hypothesis 8). Time to implementation did produce several significant effects (Figures 5.20 and 5.21). The effects were at ARL -1 versus ARL 0 (p = .0411), ARL -1 versus ARL -2 (p = .0192), and ARL -1 versus 1 (p = .0171). The coefficients indicate an increase in the probability of an ARL of -1 relative to the probability of an ARL of -2 as time to implementation increases; this supports Hypothesis 8. They also indicate that the probability of an ARL of -1 increases relative to the probability of an ARL of 1 or the probability of an ARL of 0; these effects do not support Hypothesis 8. The hypothesis appears to be supported only to the point of leaning to adoption. Time to implementation is significant in the analysis of variance (p = .0499), therefore the factor appears to help differentiate between the levels of adopters and the levels of rejecters. Because of the conflicting supports for the hypothesis, the effect of time to implementation does not appear to be a monotonic effect.

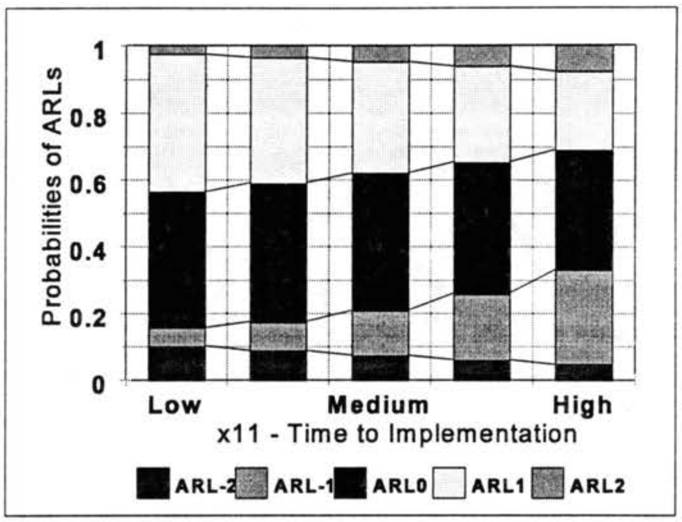

Figure 5.20. Effects of time to implementation on probabilities of ARLs (all technologies).

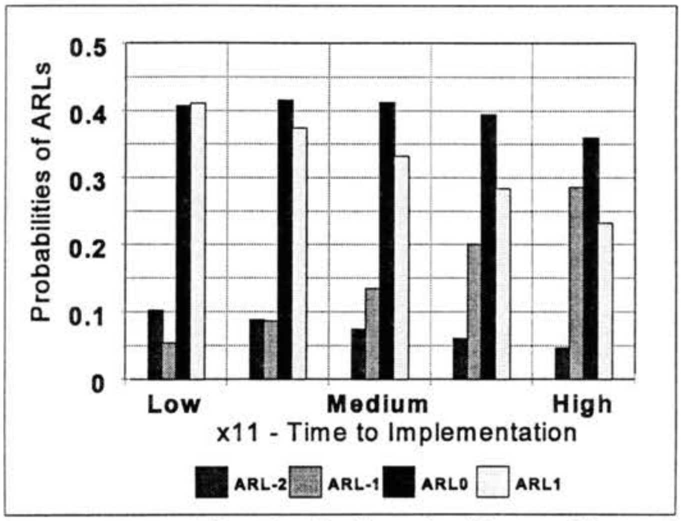

Figure 5.21. All technologies: significant effects of time to implementation on probabilities of ARLs (-1 vs 0, -1 vs -2, 1 vs -1).

Time to realization has significant effects at ARL -1 versus ARL 0 (p = .0488), ARL -1 versus ARL -2 (p = .0912), and ARL 1 versus ARL -1 (p = .0997). The last two of these effects are barely significant at the $\alpha = .10$ level. The first effect (ARL -1 versus ARL 0) and the third effect (ARL 1 versus ARL -1) support the hypothesis that increased time to realization leads to increased adoption resistance (Hypothesis 9). When benchmarked on leaning to adoption (ARL -1), the coefficients for ARLs 0 and 1 are both positive. This suggests that longer realization time produces increases in the probabilities of ARLs of 0 or 1 while decreasing the probability of an ARL of -1. The other effect, ARL -1 versus ARL -2, indicates that as realization time increases, the probability of an ARL of -1 decreases relative to the probability of an ARL of -2 (Figure 5.22). This is not consistent with Hypothesis 9. The three non-monotonic effects span four levels of the continuum and seem to help differentiate among adoption resistance levels. However, time to realization does not appear to make sufficient contribution to explaining variance in adoption resistance levels to have significance in the five-level analysis of variance.

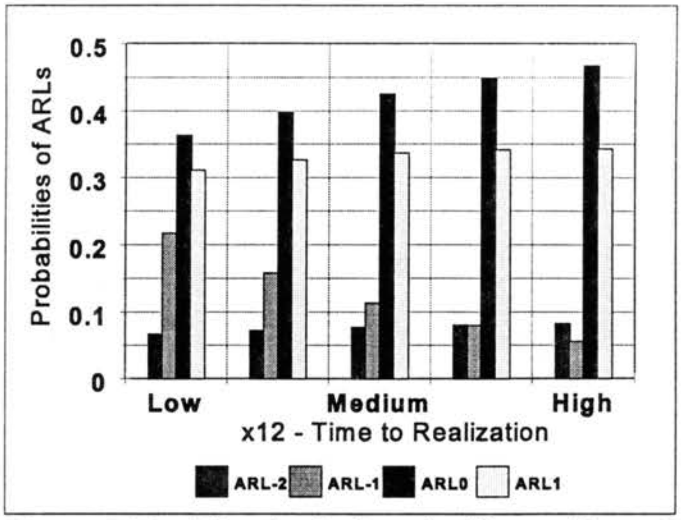

Figure 5.22. All technologies: significant effects of time to realization on probabilities of ARLs (-1 vs 0, -1 vs 2, -2 vs -1).

The last variable with significant effects in this model is difficulty of modification. As could be seen earlier in Figure 5.10, there appears to be a clear trend that higher difficulty of modification leads to higher adoption resistance as hypothesized in chapter three (Hypothesis 10). This is confirmed through the significant effects that occur in six pairs of adoption resistance levels. These effects are shown in Figure 5.23. Since the effects span the continuum, and they all show support in the same direction, it appears likely that difficulty of modification differentiates between adopters and rejecters. This is confirmed by the analysis of variance (p = 0.0036).

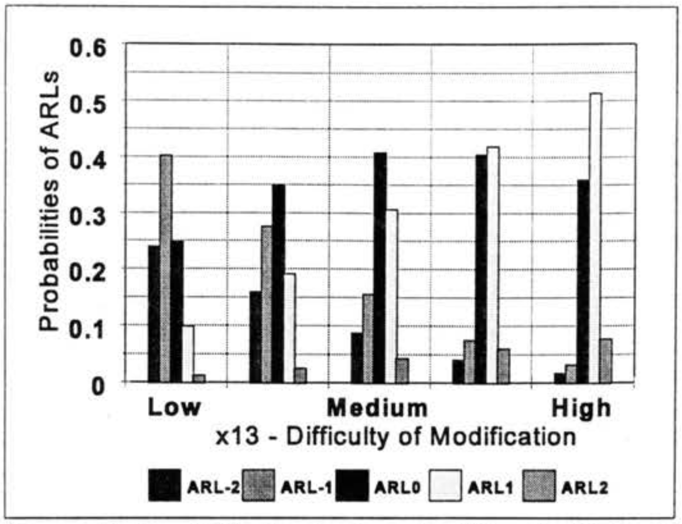

Figure 5.23. All technologies: significant effects of difficulty of modification on probabilities of ARLs (-2 vs 0, -1 vs 0, 1 vs -2, 2 vs -2, 1 vs -1, 2 vs -1).

5.4.2.1 Summary of results for all technologies, all effects

Eleven factors appear to have significant effects on the probabilities of at least two adoption resistance levels. These are summarized in Table 5.8. The variables with the largest and most consistent impacts are incompatibility, and difficulty of modification. These are the two most significant variables in the analysis of variance. Other variables that tested significant in the analysis of variance are technical expertise and time to implementation. The four factors that proved significant in the analysis of variance are considered the "main players" in differentiating between levels of adoption resistance.

Incompatibility produces nine significant effects, all supporting the hypothesis that the higher the perceived incompatibility of the technology, the higher the adoption resistance (Hypothesis 1). The effects span the continuum from adoption to rejection and appear to differentiate between adopters and rejecters of the six technologies of this research. Incompatibility was a combination of three sub-factors: how well a technology fit into the current production system, how much training was required to implement the technology and how much support upper management gave to the adoption of the technology. Therefore, it appears that technology developers can take several steps to reduce incompatibility and thereby expect a decrease in adoption resistance. First, technology developers can provide on-site training with the

Table 5.8. Spans of significant effects in the all technologies model

	Expected Direction (found the expected effect as stated in hypothesis)				Unexpected Direction (found the opposite effect from that hypothesized)			
	Spans 2 ARLs	Spans 3 ARLs	Spans 4 ARLs	Spans 5 ARLs	Spans 2 ARLs	Spans 3 ARLs	Spans 4 ARLs	Spans 5 ARLs
Past experience			(-2 v 1)					
Firm size	(0 v 1)				(1 v 2)			
Technical expertise	(-1 v 0)	(-2 v 0)			(1 v 0)			
Incommunicability					(1 v 2)	(0 v 2)	(-1 v 2)	(-2 v 2)
Non-trialability					(1 v 0)			
Discontinuity		(-2 v 0)			(1 v 2)	(0 v 2)		
Incompatibility	(1 v 0) (-1 v -2) (1 v 2)	(-2 v 0) (-1 v 1) (2 v 0)	(1 v -2) (-1 v 2)	(-2 v 2)				
Irreversibility		(0 v 2)						
Time to Implement	(-1 v -2)				(-1 v 0)	(-1 v 1)		
Time to Realization	(-1 v 0)	(-1 v 1)			(-1 v -2)			
Difficulty of Modification	(-1 v 0)	(1 v -1) (2 v 0)	(-1 v 2) (1 v -2)	(2 v -2)				

purchase/acquisition of the technology. Second, technology developers can improve efforts to convey the technology's advantages to the upper management of a firm and gain management's support for the technology. Third, technology developers can increase (when possible) the options available with a technology that make it easier to fit into a particular production line (e.g., provide a translator that will work with a selection of program languages or versions for computer controlled machinery).

Difficulty of modification also produces consistent effects across the continuum. These effects support Hypothesis 10; Hypothesis 10 suggested that the more difficult it is to modify a technology, the higher the adoption resistance. If technology developers want to reduce adoption resistance, then this set of results suggests that they should look for easier means of modifying the technology to fit into different production systems. For example, developers of thin blade saws might be able to create an adjustable fitting so the blades could be fitted onto a variety of arbors.

Technical expertise tests significant in the analysis of variance and triggers significant effects on four adoption resistance levels (three effects). Two of the effects ($p = .0283$ and $p = .0331$) support the hypothesis that the higher the technical expertise within a firm, the lower the adoption resistance up to the point of neutrality. The other effect ($p = .0070$) supports the opposite of this hypothesis. Since technical expertise appears to be significant in the analysis of variance, it appears to differentiate between the levels of adoption resistance. However, its effect is not consistent among the levels of adoption resistance. The most consistent effect of this factor is that an increase in technical expertise reduces the likelihood of a neutral position. The effects opposing the hypothesis are different from the results of the West (1990) study in which she found that more innovative firms tended to have more technical expertise.

Time to implementation is significant in the analysis of variance and produces three significant effects on the probabilities of adoption resistance levels when considered two at a time. Two of the effects ($p = .0411$, $p = .0171$) provide support opposite from that sought for the hypothesis that the longer the time to implementation, the higher the adoption resistance. The other effect ($p = .0192$) supports the hypothesis. Therefore, the data suggest that longer time to implementation is somewhat associated with reduced probability of rejection. However, longer time to implementation is also somewhat associated with reduced probability of adoption. Therefore, even though time to implementation does appear to explain variance in adoption resistance levels, it does not appear to have a monotonic effect. Earlier, it was mentioned that respondents to the pre-testing of the questionnaire seemed to answer questions regarding technologies that they had already adopted based on their actual experience rather than what their perceptions were prior to adopting the technology. Perhaps this result reflects a trend among firms leaning to rejection to underestimate the amount of time actually needed to implement the technologies in question.

Factors which show consistent support for their respective hypotheses are past experience, incompatibility, irreversibility, and difficulty of modification. Factors which show consistent support for the opposite of their respective hypotheses are incommunicability and non-trialability. Factors that have significant effects on the rejection side of the continuum but not the adoption side include irreversibility and non-trialability; Gatignon and Robertson (1989) suggest that such trends indicate that these factors may explain rejection behavior, but not adoption behavior. Several factors appear to differentiate among adoption resistance levels, but their contributions in explaining this variance are minor compared to the contributions of those factors considered the "main players." These factors include incommunicability, discontinuity, and time to realization.

5.4.2.2 Goodness-of-fit for the model involving all six technologies

A common way to test the goodness-of-fit of a multinomial logit model is to count the number of "correct" classifications (Hanneman 1997, e.g., Gatignon and Robertson 1989, Baker 1992). However, there is no standard method for deciding what constitutes a "correct" classification. For this study, a correct classification occurs when the observed ARL of a firm is also the ARL with the highest probability for that particular firm. For example, assume that the probabilities associated with ARLs of -2, -1, 0, 1, and 2 are determined to be 0.12, 0.24, 0.08, 0.21, and 0.35, respectively; a correct classification would occur if the observed ARL is 2 because the highest probability (.35) is associated with adoption resistance level 2. The correct classification rates are summarized in Table 5.9.

Table 5.9. Summary of correct classification rates (all technologies).

ARL	Number observed	Number expected	Number correct classifications	Percentage of observations correctly predicted	Percentage of correct predictions
-2	72	82	64	88.89%	78.05%
-1	42	20	11	26.19%	55.00%
0	88	105	57	64.77%	54.29%
1	89	94	58	65.17%	61.70%
2	25	15	10	40.00%	66.67%
Total	316	316	200	63.29%	63.29%

The interpretation of the classification rate is most easily accomplished by comparing these results with what would be expected if ARLs were assigned randomly. The proportional chance criterion suggests that if the ARLs were assigned randomly, only 19.3% of the classifications would be correct. Therefore, the overall correct classification rate of 63.3% implies that the model fits the data rather well. However, the level-specific correct classification rates demonstrate that the model is, in fact, very weak with respect to correctly predicting ARLs of -1.

Another indication of the goodness-of-fit of the model is the likelihood ratio. The likelihood ratio "compares the specified model with the unrestricted (saturated) model and is an appropriate goodness-of-fit test for the model" (SAS Institute Inc. 1990, p. 472). The likelihood ratio is approximately distributed as a χ^2 distribution. A χ^2 goodness-of-fit test is used to see if there are no significant differences between what was expected (expected frequencies of responses) and what was observed (observed frequencies of responses) (Downie and Heath 1965). When conducting a χ^2 goodness-of-fit test on a set of data that can be described with frequency tables showing the observed frequencies and the expected frequencies, the number of degrees of freedom is calculated as (the number of rows - one) times (the numbers of columns - 1) minus the degrees of freedom used for estimates. The likelihood ratio conducts the same type of test where each unique set of values in the X array form one row on the frequency table and the expected frequencies of each ARL (i.e., probability of each adoption resistance level times the number of adoption resistance scores associated with that set of X values) form the columns (Hanneman 1997). The number of degrees of freedom for a model where all X vectors are unique and no parameters are infinite is calculated as (number of observations - (number of independent variables) - 1)) x (response outcome categories - 1). In this data set, if all the X vectors had been unique, the degrees of freedom would have been (316 - 14 - 1)) x (5 - 1) = 1204. However, since all the X vectors were not unique, the degrees of freedom are based on the number of linearly independent X vectors (k) such that the degrees of freedom would be (k - 15) x 4 (McFadden 1974). For the model involving all six technologies, the number of linearly independent X vectors is 286, so the number of degrees of freedom is 1084. The likelihood ratio was calculated to be 644.74. $\chi^2_{644.74,\,1084} = 1.00$, so the likelihood ratio is insignificant, indicating that the differences between the observed frequencies and the expected frequencies in the frequency table are not so large that they could not have happened by chance. This is interpreted to mean that the model fits the data well.

5.5. Level 2 - Technologies grouped by "hardness"

The analysis was conducted with the technologies grouped by hardness. There were three hard technologies and three soft technologies, so two data sets were formed based on this distinction. First, a discussion on the results of the analysis involving the hard technologies of thin saw kerf technology, CNC machining, and water-based finishes is presented. A discussion concerning the analysis of the soft technologies as a group follows in section 5.5.2.

5.5.1 Hard technologies

The scope of this phase of the analysis consisted of the three hard technologies (thin saw kerf, CNC machining, and water-based finishes). Again, five response outcomes were possible, so the minimum number of observations needed for meaningful analysis was 80. The total number of observations for this analysis was 181. Results of the survey (observed results) are given in Table 5.10.

Table 5.10. Observed levels of adoption resistance (hard technologies)

Adoption resistance level (response)	Frequency of response
Adoption	41
Leaning towards adoption	24
Neutral	48
Leaning to rejection	52
Rejection	16
Total	181

As before, results of the multinomial logit analysis benchmarked on the neutral position are presented, followed by the overall results of all five cases; finally a summary of the effects that tested significant in the analysis of variance is presented.

5.5.1.1. Hard technologies, benchmarked on neutral

Results of the multinomial logit analysis when benchmarked on neutral are given in Table 5.11. The null hypothesis being tested is that all the variables are nonrelevant (i.e., Ho: $\beta_{ij} = 0 \ \forall \ \beta_{ij}$, i = 0, ..., 14, j = -2, ..., 2).

Table 5.11. Logit analysis of factors affecting the probability of adoption resistance level, benchmarked on the neutral case (hard technologies)

	Adoption (j = -2)		Lean to Adoption (j = -1)	
	estimate	p-value	estimate	p-value
Intercept (β_{0j})	5.0415	.2943	-1.0097	.8859
β_{1j} Technical progressiveness.1	.3096	.7337	.7380	.3997
β_{2j} Technical progressiveness.2	-1.4294	.1532	-.2165	.8277
β_{3j} Past experiences	1.2321	.2798	-.5345	.6039
β_{4j} Firm size	-9.5253	.1955	-8.7489	.2956
β_{5j} Technical expertise	18.6663	.0159**	9.3511	.2456
β_{6j} Incommunicability	-2.4563	.0471**	-1.8820	.1096
β_{7j} Non-trialability	-.7468	.4673	-.0922	.9323
β_{8j} Discontinuity	-.8395	.0723***	-.7371	.1022
β_{9j} Incompatibility	-1.8715	.1729	-.0635	.9616
β_{10j} Irreversibility	1.1439	.1778	-.1341	.8774
β_{11j} Time to implement	.0431	.9480	1.0938	.0532***
β_{12j} Time to realization	.9204	.1366	-.3451	.5302
β_{13j} Difficulty of modification	-2.3445	.0100*	-1.7569	.0317**
β_{14j} Indivisibility	-.0217	.9783	.9696	.2560

* indicates significance at the $\alpha = .01$ level
** indicates significance at the $\alpha = .05$ level
*** indicates significance at the $\alpha = .10$ level

Table 5.11. Continued

	Lean to Rejection (j = 1)		Rejection (j = 2)	
	estimate	p-value	estimate	p- value
Intercept (β_{0j})	-3.0723	.7327	8.7617	.3621
β_{1j} Technical progressiveness.1	-.2919	.6899	.6459	.5975
β_{2j} Technical progressiveness.2	-.9302	.5509	-1.3720	.5769
β_{3j} Past experiences	-.8443	.3058	.4639	.7129
β_{4j} Firm size	-15.5505	.1183	1.8507	.8399
β_{5j} Technical expertise	13.3373	.0912***	11.1041	.3494
β_{6j} Incommunicability	-1.8509	.0815***	-3.7543	.0163**
β_{7j} Non-trialability	-1.4486	.1458	-.7070	.6042
β_{8j} Discontinuity	-.6267	.1232	-1.7155	.0133**
β_{9j} Incompatibility	4.3851	.0002*	6.6188	.0003*
β_{10j} Irreversibility	.4742	.5423	.6212	.5554
β_{11j} Time to implement	.1622	.7291	.7530	.3354
β_{12j} Time to realization	-.4395	.3868	.5310	.5118
β_{13j} Difficulty of modification	.3711	.5758	-.5334	.6038
β_{14j} Indivisibility	.4817	.5453	2.1622	.0648***

* indicates significance at the $\alpha = .01$ level
** indicates significance at the $\alpha = .05$ level
*** indicates significance at the $\alpha = .10$ level

Incommunicability (x_6) appears to be significant for three levels of adoption resistance and nearly significant at the fourth. When a factor appears to be significant at more than one level, a graphical analysis of the elasticity of that factor aids in understanding the results. Holding all other variables at their means, incommunicability was varied from low to high (Figure 5.24).

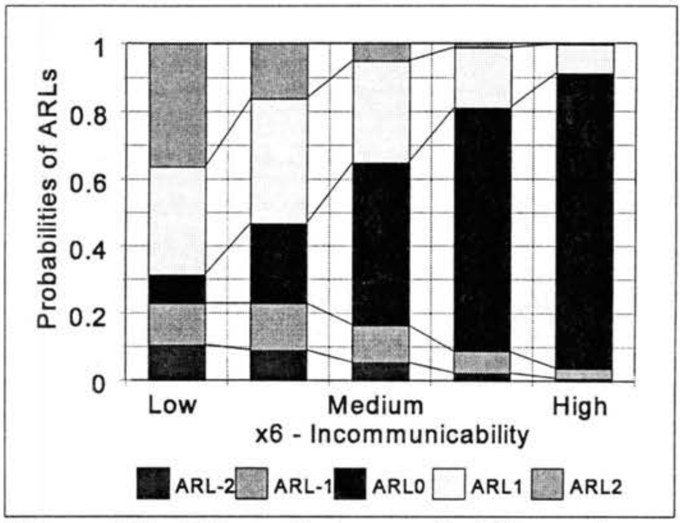

Figure 5.24. Effect of incommunicability on the probabilities of ARLs (hard technologies).

As incommunicability increases, the probabilities of adoption, leaning to rejection and rejection all decrease significantly. At the same time, the probability of a neutral position significantly increases. Therefore, there appears to be support for the hypothesis that higher incommunicability leads to higher adoption resistance (Hypothesis 7) up to the point of neutrality. Then, the empirical evidence suggests the opposite of the hypothesis by demonstrating that additional incommunicability leads to a decrease in leaning to reject and rejection.

Incompatibility appears to be significant with respect to ARLs of 1 and 2. The positive coefficients on both of these levels indicates that an increase in incompatibility results in increases in both probabilities of an ARL of 1 or 2 (leaning to rejection or rejection). The probabilities of each ARL as incompatibility is varied are shown in Figure 5.25. The significant effects are depicted in Figure 5.26.

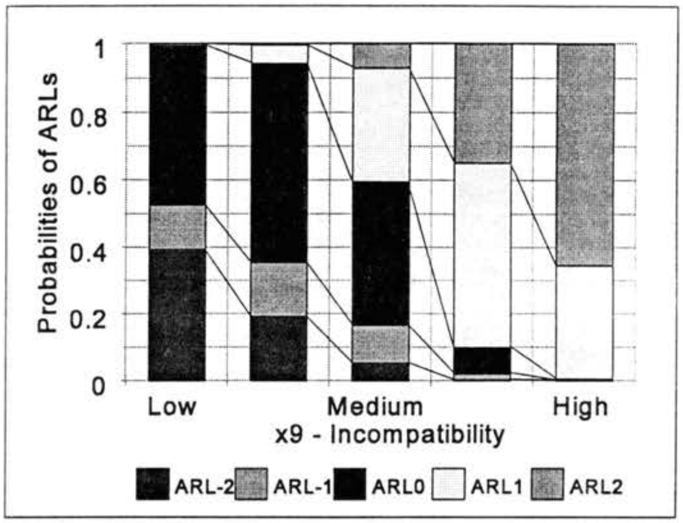

Figure 5.25. Effects of incompatibility on the probabilities of ARLs (hard technologies).

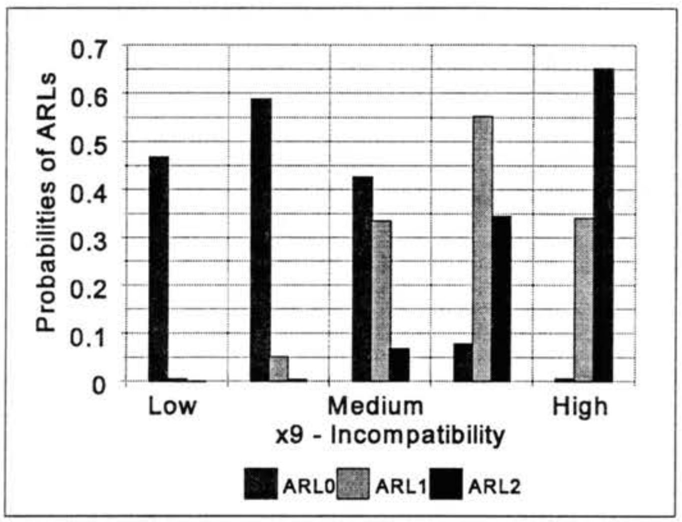

Figure 5.26. Significant effects of changes in incompatibility on the probabilities of ARLs (hard technologies, benchmarked on the neutral case).

The increases in the probabilities of ARLs 1 and 2 drive the probabilities of ARLs of -2, -1, and 0 to zero, providing vast support that higher incompatibility is associated with higher adoption resistance (Hypothesis 1).

The negative signs on the coefficients associated with discontinuity indicate that the firm's perception of the discontinuity of a technology has a negative, significant effect on the probability of ARLs of -2 or 2 versus an adoption resistance level (ARL) of 0. This implies that higher discontinuity may be associated with higher probability of a neutral position. To check this conclusion, the level of discontinuity was varied from low to high while holding all other variables constant at their means (Figure 5.27).

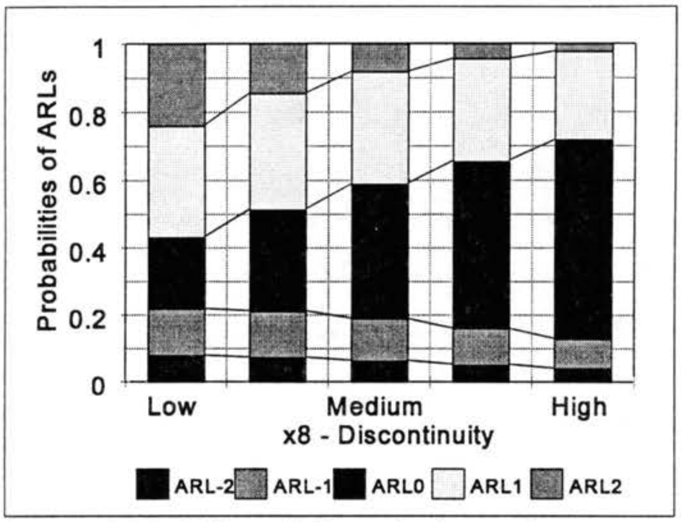

Figure 5.27. Effect of discontinuity on the probabilities of ARLs (hard technologies).

This is a case where an increase in discontinuity appears to result in higher adoption resistance to the point of neutrality. For levels of adoption resistance beyond neutrality, increases in discontinuity appear to effect decreases in probabilities of higher ARLs. Therefore, there appears to be support for Hypothesis 2 (The higher the level of discontinuity of a technology, the higher the adoption resistance) in the adoption to neutral range but not in the neutral to rejection range.

The number of engineers a firm employed (technical expertise of a firm) appears to be positively significant on the probability of adoption (ARL -2) versus the probability of neutrality (ARL 0). However, the number of engineers also appears to be positively significant on the probability of leaning to rejection (ARL 1) versus the probability of neutrality (ARL 0). This suggests that the higher the technical expertise as measured by the number of engineers employed by a firm, the less likely that firm is to have a neutral opinion on adopting hard technologies.

As can be seen in Figure 5.28, the probability of a neutral position goes to zero very quickly as the number of engineers increases. The probability of adoption (ARL -2) increases at a much faster rate than the probability of leaning to rejection (ARL 1) and, in fact, forces the probability of leaning to rejection to approach zero (Figures 5.28 and 5.29). Therefore, the data support the hypothesis that higher levels of technical expertise as measured by number of engineers are associated with lower adoption resistance (Hypothesis 16).

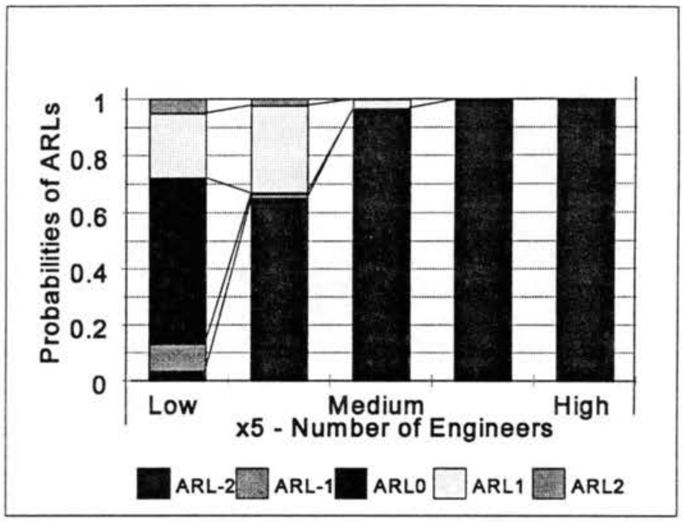

Figure 5.28. Effects of number of engineers on the probabilities of ARLs (hard technologies).

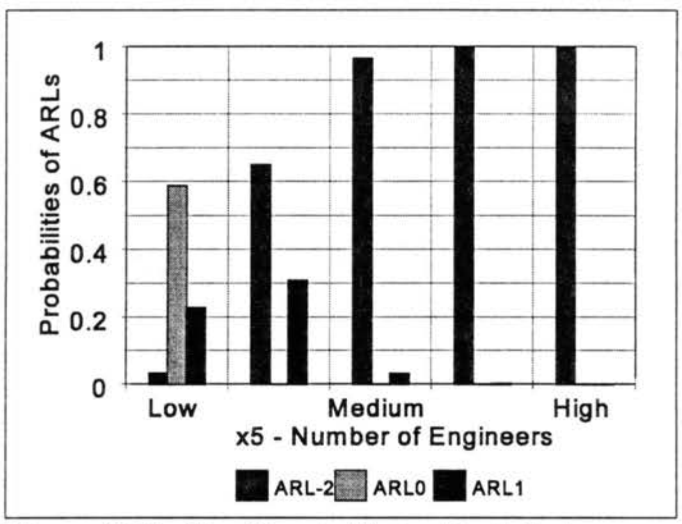

Figure 5.29. Significant effects of technical expertise on the probabilities of ARLs (hard technologies, benchmarked on the neutral case).

Difficulty of modification appears to be significant with respect to both the adoption level and the leaning to adoption level. The negative coefficients indicate that as the difficulty of modification increases, the probability of ARLs of -2 or -1 decrease. Therefore, the probability of an ARL of 0, 1, or 2 increases, and Hypothesis 10 is supported. The effects of changes in difficulty of modification are shown in Figure 5.30.

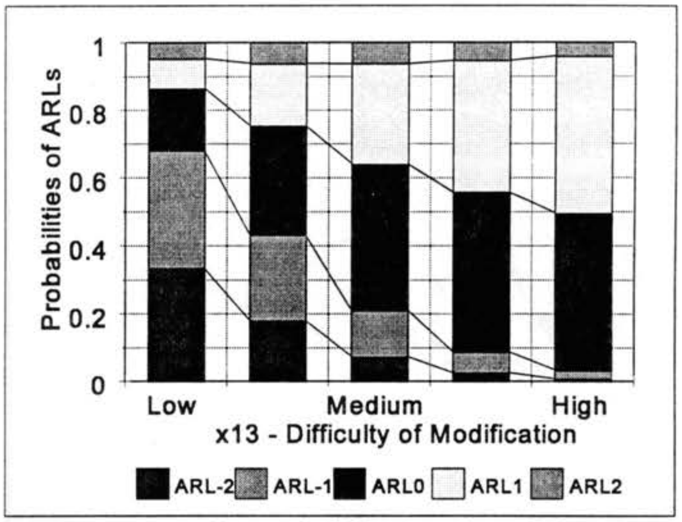

Figure 5.30. Effects of difficulty of modification on probabilities of ARLs (hard technologies).

Time to implementation appears to be significant with respect to the ARL of -1. The positive coefficient implies that an increase in the time to implementation leads to an increase in the likelihood of an ARL of -1 versus an ARL of 0. This suggests that an increase in the time to implementation is associated with lower adoption resistance as reflected in Figure 5.31. This is opposite from what is suggested in Hypothesis 8 (The longer the time to implementation of a technology, the higher the adoption resistance).

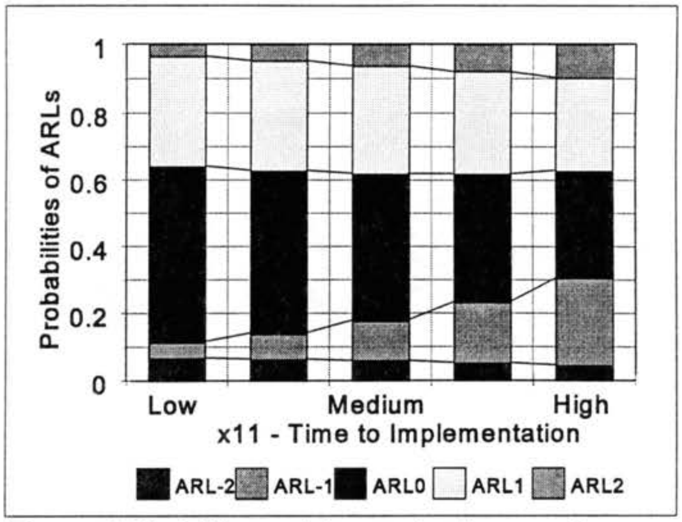

Figure 5.31. Effects of time to implementation on probabilities of ARLs (hard technologies).

The last variable to have a significant effect indicated is indivisibility. The effect is significant with respect to an ARL of 2. The significant effect of indivisibility has a positive coefficient that indicates an increased probability of an ARL of 2 versus an ARL of 0 as indivisibility increases. This suggests that increased indivisibility is associated with higher adoption resistance and Hypothesis 4 (The higher the indivisibility of the technology, the higher the adoption resistance) is supported.

5.5.1.2 Hard technologies, all effects

To get a complete picture of the model and its significant effects, the same type of analysis must be conducted with each adoption resistance level assuming the benchmarking position. Factors which appear to be significant ($\alpha = .10$) when considering two adoption resistance levels at a time include past experience, firm size, number of engineers, incommunicability, discontinuity, incompatibility, time to implementation, time to realization, difficulty of modification, and indivisibility. Coefficients and p-values are given in Appendix G. A summary of the analysis of variance is given in Table 5.12. The factors that have significant effects in the analysis of variance are incompatibility, difficulty of modification, discontinuity, and incommunicability.

Table 5.12. Analysis of variance of hard technologies model

Source	p-value
Intercept	.5931
Technical progressiveness.1	.7963
Technical progressiveness.2	.6131
Past experiences	.3700
Firm size	.3096
Technical expertise	.1595
Incommunicability	.0887***
Non-trialability	.6072
Discontinuity	.0824***
Incompatibility	.0000*
Irreversibility	.5978
Time to implementation	.3101
Time to realization	.2141
Difficulty of modification	.0255**
Indivisibility	.3052

*Significant at $\alpha = .01$ level
**Significant at $\alpha = .05$ level
***Significant at $\alpha = .10$ level

Past experience appears to be significant with respect to ARL 1 versus ARL -2 (leaning to rejection versus adoption). When benchmarking on ARL -2 the coefficient is negative. This implies that an increase in satisfaction with past experience leads to a decrease in the probability of an ARL of 1 versus the probability of an ARL of -2 (Figure 5.32). In other words, the probability of an ARL of -2 increases and higher satisfaction with past experience is associated with lower adoption resistance. Therefore, the hypothesis that the less favorable a manufacturer's experience with earlier technologies, the higher the adoption resistance (Hypothesis 13) is supported by the data concerning hard technologies.

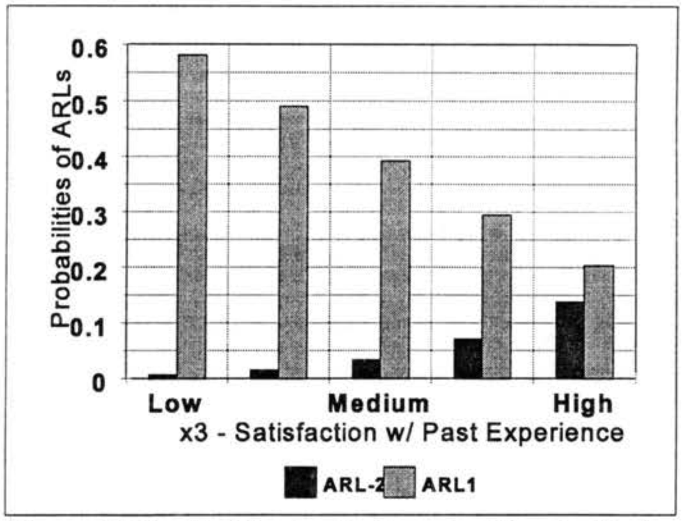

Figure 5.32. Hard technologies: significant effects of past experience on ARLs (1 vs -2).

Firm size was expected to have a negative relationship with adoption resistance. It was expected that smaller firm size would be associated with higher adoption resistance (Hypothesis 15). Firm size is significant with respect to leaners to rejection and rejecters (ARL 1 versus ARL 2). When benchmarking on ARL 1, the coefficient has a positive sign indicating that increased firm size results in an increase in the probability of an ARL of 2 compared to the probability of an ARL of 1 (Figure 5.33). This is the opposite from what was expected.

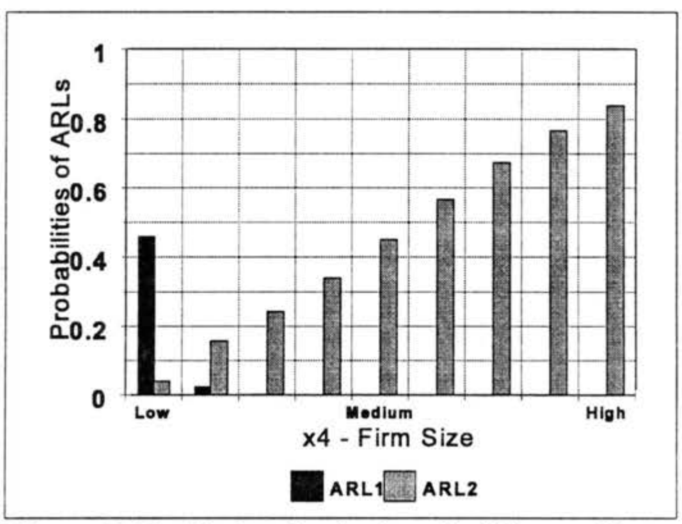

Figure 5.33. Hard technologies: significant effects of firm size on probabilities of ARLs (1 vs 2).

Technical expertise, as measured by the number of engineers employed, was expected to be negatively associated with adoption resistance. Hypothesis 16 suggested that lower technical expertise would lead to higher adoption resistance. Number of engineers appears to be significant at the adoption versus neutral comparison and the leaning to rejection versus neutral comparison. Since both effects involve the neutral level of adoption resistance, the above discussion (at Figures 5.28 and 5.29) covers the entire effect of the number of engineers. The effects that are detected both have positive coefficients when the benchmark is neutral despite the fact that each of the effects involves an adoption resistance level on opposite sides of the neutral position. Therefore, some support exists for Hypothesis 16 to the point of neutrality, but there is also support for the opposite of Hypothesis 16. The two effects span four levels of adoption resistance suggesting that technical expertise may help differentiate among adoption resistance levels. The contribution of technical expertise in explaining adoption resistance level variance appears to be eclipsed by other, more significant factors.

Incommunicability has significant effects at ARL -2 versus ARL 0, ARL 1 versus ARL 0 and ARL 2 versus ARL 0. Once again, the above discussion on the case where the benchmark position is the neutral position covers all the significant effects triggered by this factor. As incommunicability increases, probabilities of ARLs -2, 1, or 2 decrease relative to the probability of an ARL of 0 (Figure 5.24). Even though the direction of change of the probabilities is the same for adoption resistance levels on both sides of the neutral position, incommunicability tests significant in the analysis of variance. Therefore, it appears to be a driver in explaining variance in adoption resistance levels, but its effect does not appear to be monotonic. This is further confirmed by the fact that none of the effects span the neutral position (e.g., -2 versus 2 or -2 versus 1). As mentioned before, the decrease in ARL -2 as incommunicability increases provides some limited support for Hypothesis 7 (the higher the incommunicability of the technology, the higher the adoption resistance).

Discontinuity appears to be significant with respect to four levels of adoption resistance. The effect of discontinuity is significant at ARL -2 versus ARL 0 (-.8395, p = .0723), ARL 2 versus ARL 1 (-1.088, p = .0929), and ARL 2 versus ARL 0 (-1.7155, p = .0133). The effect of changes in discontinuity are shown in Figure 5.27. The negative coefficients at ARL -2 versus ARL 0 and ARL 2 versus ARL 0 indicate that as discontinuity increases, the probability of an ARL of -2 decreases relative to the probability of an ARL of 0 *and* the probability of an ARL of 2 decreases relative to the probability of an ARL of 0; therefore, the probability of a neutral position increases. The coefficients also indicate that the probability of an ARL of 2 (rejection) decreases relative to the probability of an ARL of 1 (leaning to rejection). These effects are confirmed by the graph shown in Figure 5.34. The decrease in probability of an ARL of -2 versus an ARL of 0, indicates support for the hypothesis that higher discontinuity leads to higher adoption resistance (Hypothesis 2) to the point of neutrality. However, once the neutral position is reached, increases in discontinuity seem to lead to lower adoption resistance. Through analysis of variance, it appears that discontinuity explains variance in adoption resistance levels (p = .0824), but it does not do so in a uniform manner from adoption to rejection.

Incompatibility appears to be significant in the probabilities of adoption resistance levels in the following comparisons: ARL 1 versus ARL 0 (4.3851, p = .0002), ARL 2 versus ARL 0 (6.6188, p =

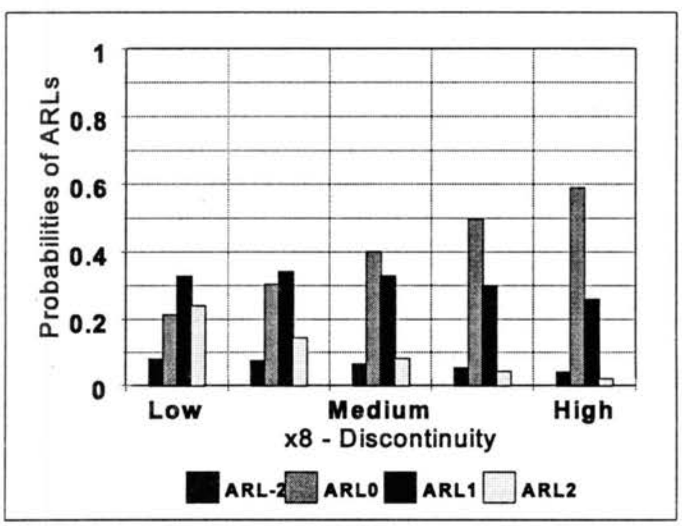

Figure 5.34. Hard technologies: significant effects of discontinuity on the probabilities of ARLs (-2 vs 0, 2 vs 0, and 2 vs 1).

.0003), ARL 1 versus ARL -2 (6.2566, p = .0000), ARL 2 versus ARL -2 (8.4903, p = .0000), and ARL 2 versus ARL -1 (6.6823, p = .0009). Therefore, all adoption resistance levels are considered in determining the overall effect of incompatibility. In essence, the five positive coefficients indicate that an increase in incompatibility leads to:

> an increase in the probability of an ARL of 1 relative to the probability of an ARL of 0;
> an increase in the probability of an ARL of 2 relative to the probability of an ARL of 0;
> an increase in the probability of an ARL of 1 relative to the probability of an ARL of -2;
> an increase in the probability of an ARL of 2 relative to the probability of an ARL of -2; and
> an increase in the probability of an ARL of 2 relative to the probability of an ARL of -1.

Figures 5.24 and 5.35 show that higher incompatibility is associated with higher adoption resistance, supporting Hypothesis 1. Since the effects span the continuum, it seems likely that incompatibility may help differentiate between adopters and rejecters. This is confirmed through the analysis of variance where incompatibility has a highly significant effect (p = .0000).

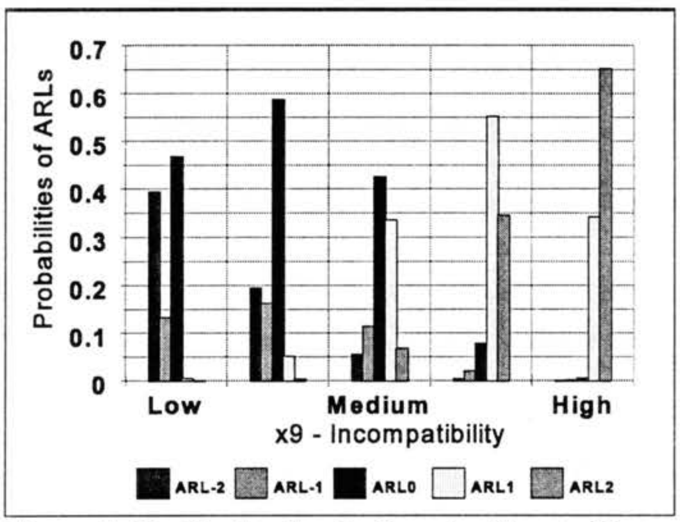

Figure 5.35. Hard technologies: significant effects of incompatibility on probabilities of ARLs (1 vs 0, 2 vs 0, 1 vs -2, 2 vs -2, 1 vs -1, 2 vs -1).

Time to implementation appears to be significant only at ARL -1 versus ARL 0 (1.0938, p = .0532). Therefore, the earlier conclusion that the data suggest an increase in the time to implementation may be associated with lower adoption resistance still holds (Figures 5.31 and 5.36). Since this was the only significant effect of time to implementation, it seems unlikely that this factor differentiates between adopters and rejecters, nor does it support Hypothesis 8 (The longer the time to implementation, the higher the adoption resistance).

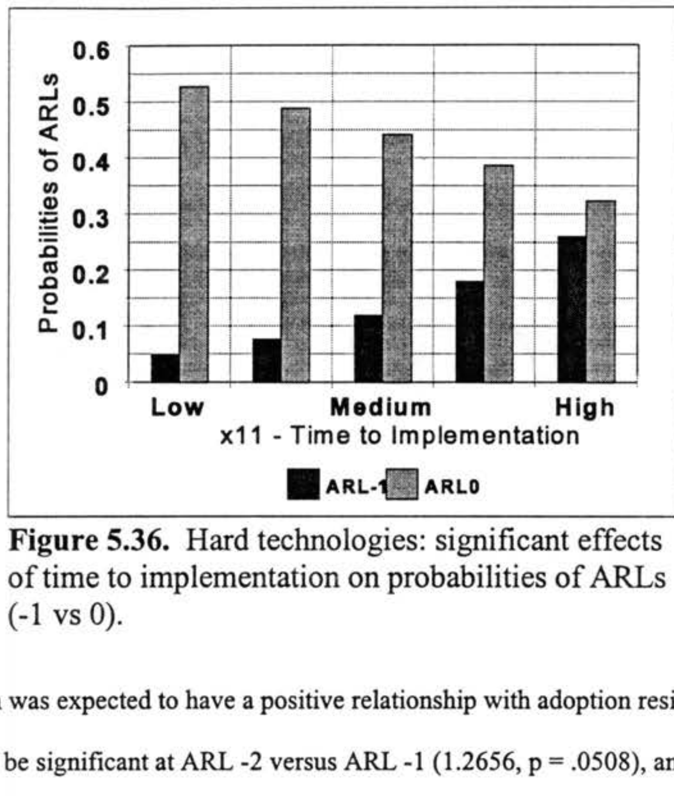

Figure 5.36. Hard technologies: significant effects of time to implementation on probabilities of ARLs (-1 vs 0).

Time to realization was expected to have a positive relationship with adoption resistance (Hypothesis 9). This factor appears to be significant at ARL -2 versus ARL -1 (1.2656, p = .0508), and ARL -2 versus ARL 1 (1.3599, p = .0480). These effects are shown in Figure 5.37. As time to realization increases, the probability of an ARL of -2 increases relative to the probabilities of ARLs of -1 or 1. Looking at it from the other benchmark levels, the probabilities of ARLs of -1 or 1 decrease relative to the probability of an ARL of -2. This suggests support for the opposite of Hypothesis 9 (The longer the realization time of a technology, the higher the adoption resistance). Since the effects span four levels of the continuum and specifically involve three adoption resistance levels, it appears that time to realization may contribute to differentiating among adoption resistance levels. However, this contribution does not appear to be significant in the five-level analysis of variance.

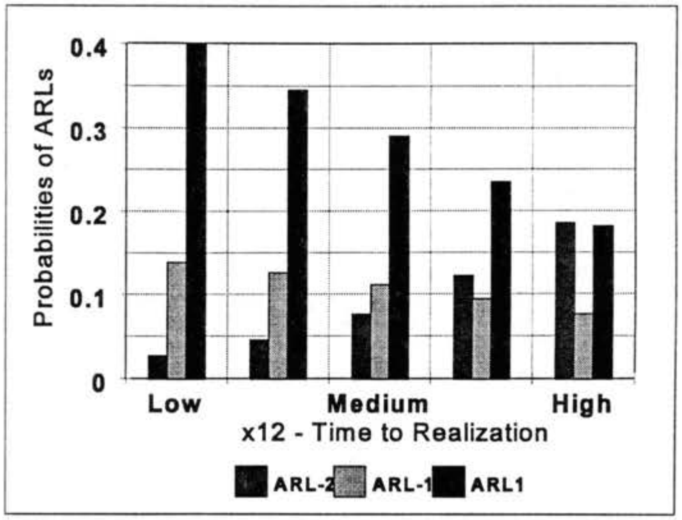

Figure 5.37. Hard technologies: significant effects of time to realization on probabilities of ARLs (-1 vs -2, 1 vs -2).

Difficulty of modification has significant effects at ARL -2 versus ARL 0 (-2.3445, $p = .0100$), ARL -1 versus ARL 0 (-1.7569, $p = .0317$), ARL 1 versus ARL -2 (2.7157, $p = .0046$), and ARL 1 versus ARL -1 (2.1281, $p = .0125$). The overall effect is shown in Figure 5.30 and shows that as difficulty of modification increases, adoption resistance increases. The significant effects can be interpreted more easily in Figure 5.38. Increases in difficulty of modification lead to increases in the probability of an ARL of 1 relative to the probability of an ARL of -2; increases in the probability of an ARL of 1 relative to the probability of an ARL of -1; decreases in the probability of an ARL of -2 relative to the probability of an ARL of 0; and decreases in the probability of an ARL of -1 relative to the probability of an ARL of 0. As difficulty increases, the probabilities of ARLs of -2 or -1 decrease and approach zero and the probability of an ARL of 1 increases. The data related to hard technologies provide a good deal of support for the hypothesis that increased difficulty of modification leads to higher adoption resistance (Hypothesis 10). Since the effects nearly span the continuum, it appears that difficulty of modification probably helps differentiate between adopters and those who lean toward rejection; this is confirmed by the significance of the factor in the analysis of variance.

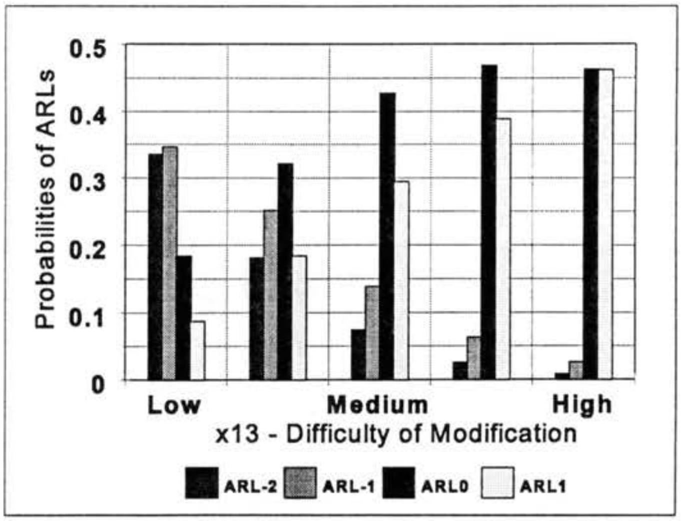

Figure 5.38. Hard technologies: significant effects of difficulty of modification on probabilities of ARLs (-2 vs 0, -1 vs 0, 1 vs -2, 1 vs -1).

The final factor that appears to be significant in at least one (two) of the analyses was indivisibility. Significant effects were discovered at ARL 0 versus ARL 2 (-2.1622, p = .0648), and ARL -2 versus ARL 2 (-2.1838, p = .0752). The coefficients indicate that as indivisibility increases, the probability of a neutral position decreases relative to the probability of rejection. Similarly, the probability of adoption decrease relative to the probability of rejection (Figure 5.39). Therefore, there is support for the hypothesis (Hypothesis 4) that increased indivisibility increases adoption resistance when it comes to hard technologies. The effects span all five levels of resistance and appear to differentiate among different levels of adoption resistance. However, indivisibility does not appear to be significant in the analysis of variance, suggesting that indivisibility's differentiating ability is overshadowed by the ability of other variables to explain variance in adoption resistance levels.

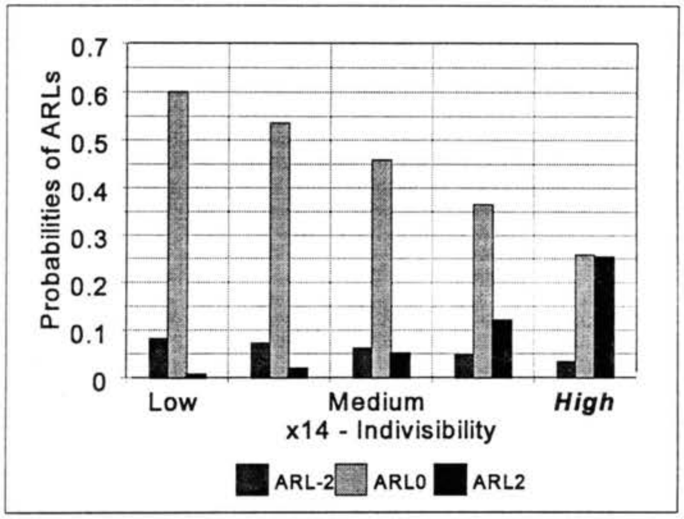

Figure 5.39. Hard technologies: significant effects of indivisibility on probabilities of ARLs (0 vs 2 and -2 vs 2).

5.5.1.3 Summary of results for hard technologies, all effects

Ten factors appear to have significant effects on the probabilities of at least two adoption resistance levels. These are summarized in Table 5.13. The variables that have significant effects on the overall model, as determined through analysis of variance, are incompatibility (p = .0000), difficulty of modification (p = .0255), discontinuity (p = .0824), and incommunicability (p = .0887).

Incompatibility produces five significant effects, all supporting the hypothesis that the higher the perceived incompatibility of the technology, the higher the adoption resistance (Hypothesis 1). The effects span the continuum from adoption to rejection and appear to differentiate between adopters and rejecters of the three hard technologies of this research. Incompatibility was a combination of three sub-factors: how well a technology fit into the current production system, how much training was required to implement the technology and how much support upper management gave to the adoption of the technology. Therefore, it appears that hard technology developers can take several steps to reduce incompatibility and thereby

Table 5.13. Spans of significant effects in the hard technologies model

	Expected Direction (found the expected effect as stated in hypothesis)				Unexpected Direction (found the opposite effect from that hypothesized)			
	Spans 2 ARLs	Spans 3 ARLs	Spans 4 ARLs	Spans 5 ARLs	Spans 2 ARLs	Spans 3 ARLs	Spans 4 ARLs	Spans 5 ARLs
Past experience			(-2 v 1)					
Firm size					(1 v 2)			
Technical expertise		(-2 v 0)			(1 v 0)			
Incommunicability		(-2 v 0)			(1 v 0)	(0 v 2)		
Discontinuity		(-2 v 0)			(1 v 2)	(0 v 2)		
Incompatibility	(1 v 0)	(2 v 0)	(1 v -2) (-1 v 2)	(-2 v 2)				
Time to Implement					(-1 v 0)			
Time to Realization					(-1 v -2)		(-2 v 1)	
Difficulty of Modification	(-1 v 0)	(1 v -1) (-2 v 0)	(1 v -2)					
Indivisibility		(0 v 2)		(-2 v 2)				

expect a decrease in adoption resistance. First, hard technology developers can provide on-site training with the purchase/acquisition of the technology. Second, technology developers can improve efforts to convey the hard technology's advantages to the upper management of a firm and gain management's support for the technology. Third, hard technology developers can increase (when possible) the options available with a technology that make it easier to fit into a particular production line.

Difficulty of modification produces consistent effects across four levels of the continuum. These effects support Hypothesis 10 up to the point of leaning to rejection; Hypothesis 10 suggested that the more difficult it is to modify a technology, the higher the adoption resistance. If hard technology developers want to reduce adoption resistance, then this set of results suggests that they should look for easier means of modifying the technology to fit into different production systems.

Discontinuity produces two significant effects that are consistent in their support for the opposite of Hypothesis 2 (The higher the level of discontinuity, the higher the adoption resistance). It also produces one effect that supports the hypothesis. Since the effects are not consistent in their support of the hypothesis, it does not appear that discontinuity is a determinant driver in explaining the variance in adoption resistance levels.

Like discontinuity, incommunicability produces two significant effects that are consistent in their support for the opposite of Hypothesis 7 (The higher the incommunicability of the technology, the higher the adoption resistance). It also produces one effect that supports the hypothesis. Since these effects are not consistent in their support of the hypothesis, it does not appear that the effect of incommunicability is uniform in its effect on the overall model.

Factors that consistently support their associated hypotheses include past experience, incompatibility, difficulty of modification, and indivisibility. Factors that consistently show support for the opposite of their associated hypotheses are firm size, time to implement, and time to realization. Firm size is the only factor that appears to explain some level of rejection behavior but no levels of adoption behavior. Time to realization appears to explain some level of adoption behavior but no levels of rejection behavior.

Factors that appear to have some effect in differentiating among adoption resistance levels, but do not appear to be significant in the analysis of variance include technical expertise, time to realization, and indivisibility. the ability of these factors to differentiate among adoption resistance levels appears to be overshadowed by the factors that appear to be significant in the analysis of variance.

5.5.1.4 Goodness-of-fit for the hard technologies model

Again, correct classification rates were computed to determine the goodness-of-fit of the model for this phase of the analysis. The correct classification rates are summarized in Table 5.14.

Table 5.14. Summary of correct classification rates for the hard technologies model.

ARL	Number observed	Number expected	Number correct classifications	Percentage of observations correctly predicted	Percentage of correct predictions
-2	41	44	35	85.37%	79.55%
-1	24	14	5	20.83%	35.71%
0	48	57	30	62.50%	52.63%
1	52	57	36	69.23%	63.16%
2	16	9	7	43.75%	77.78%
Total	181	181	113	62.43%	62.43%

As mentioned before, the interpretation of the classification rate is most easily accomplished by comparing these results with what would be expected if ARLs were assigned randomly. The proportional chance criterion suggests that if the ARLs were assigned randomly, only 23.6% of the classifications would be correct. Therefore, the overall correct classification rate of 62.4% implies that the model fits the data rather well. However, the level-specific correct classification rates demonstrate that the model is weak with respect to correctly predicting ARLs of -1.

The likelihood ratio of this model is 358.10 with 169 linearly independent X vectors. Therefore, a total of 676 degrees of freedom are available; sixty β coefficients are estimated using one degree of freedom each and leaving 616 degrees of freedom for the likelihood ratio. Since the likelihood ratio is approximately distributed as a χ^2 distribution, the likelihood ratio is not significant ($p = 1.00$) and thus, it is determined that the model fits the hard technologies data well.

5.5.2. Soft technologies

This part of the study involves data concerning the three soft technologies (self-managed work teams, statistical process control, and pc-based production control). The total number of observations for this analysis was 135, meeting the minimum number of observations criterion (80 observations). Results of the survey (observed results) are given in Table 5.15.

Table 5.15. Observed levels of adoption resistance (soft technologies).

Adoption resistance level (response)	Frequency of response
Adoption	31
Leaning towards adoption	18
Neutral	40
Leaning to rejection	37
Rejection	9
Total	135

Significant results of the multinomial logit analysis when benchmarking on the adoption level (ARL -2) are given in Table 5.16. As in the other applications of the model, the null hypothesis being tested is that all the variables are nonrelevant (i.e. Ho: $\beta_{ij} = 0 \ \forall \ \beta_{ij}$, $i = 0, \ldots, 14$, $j = -2, \ldots, 2$).

Table 5.16. Significant results of factors affecting the probability of adoption resistance levels when benchmarking on adoption (soft technologies).

	Lean to Adoption (j = -1)		Neutral (j = 0)		Lean to Rejection (j = 1)		Rejection (j = 2)	
	estimate	p-value	estimate	p-value	estimate	p-value	estimate	p-value
β_{1j} Technical progressiveness.1	2.4292	.1301	6.0644	.0011**	4.1051	.0306**	7.7858	.0086*
β_{2j} Technical progressiveness.2	-.6937	.8149	-10.3550	.0754***	-6.3443	.2156	-4.5765	.5390
β_{3j} Past experiences	.1812	.9149	-3.2084	.0650***	-3.0248	.0971***	-.7387	.8034
β_{5j} Technical expertise	.0864	.9916	-27.4016	.0733***	-.9925	.9427	-18.9641	.4089
β_{6j} Incommunicability	-.3047	.8282	-4.0505	.0416**	-1.2495	.5430	-6.3133	.0940***
β_{7j} Non-trialability	-.7149	.6151	1.8425	.3299	.5887	.7670	7.2490	.0412**
β_{8j} Discontinuity	.9991	.1054	1.2430	.1078	1.7357	.0215**	.5582	.7655
β_{9j} Incompatibility	6.5934	.0272**	14.5132	.0002*	13.4415	.0006*	19.8075	.0002*
β_{10j} Irreversibility	1.1149	.3286	-3.4066	.0322**	-1.2166	.4549	1.1530	.6346
β_{11j} Time to implement	2.0643	.0918***	1.3307	.3279	.1095	.9357	3.4759	.1284
β_{12j} Time to realization	-.4083	.6851	3.2461	.0280**	3.8025	.0148**	2.6348	.1740
β_{13j} Difficulty of modification	-.7540	.5528	.6463	.5596	2.3537	.0480**	5.5441	.0522***
β_{14j} Indivisibility	-.9056	.3545	-4.0035	.0252**	-2.5420	.1446	-7.8614	.0047*

* indicates significance at the $\alpha = .01$ level
** indicates significance at the $\alpha = .05$ level
*** indicates significance at the $\alpha = .10$ level

The analysis of variance is summarized in Table 5.17.

Table 5.17. Analysis of variance for the soft technologies model

Source	p-value
Intercept	.0908
Technical progressiveness.1	.0114**
Technical progressiveness.2	.4536
Past experiences	.2415
Firm size	.4492
Technical expertise	.2830
Incommunicability	.1178
Non-trialability	.1968
Discontinuity	.1870
Incompatibility	.0025*
Irreversibility	.0176**
Time to implementation	.0894***
Time to realization	.0490**
Difficulty of modification	.0406**
Indivisibility	.0535***

* Significant at $\alpha = .01$ level
** Significant at $\alpha = .05$ level
*** Significant at $\alpha = .10$ level

Conducting the multinomial logit analysis with each adoption resistance level as the benchmark level provides a complete set of all the significant effects (coefficients and p-values of significant effects are recorded in Appendix H). In this analysis of the soft technology data set, each of the fourteen variables appear in the significant effects.

Technical progressiveness.1 appears to be significant with respect to all five levels of adoption resistance. In particular, technical progressiveness.1 tested significant in its effect on the probability of adoption versus neutral ($p = .0011$), adoption versus leaning to rejection ($p = .0306$), adoption versus rejection ($p = .0086$), leaning to adoption versus neutral ($p = .0502$), leaning to adoption versus rejection ($p = .0710$), and neutral versus leaning to rejection ($p = .0592$). The changes in probabilities of each ARL are shown in Figures 5.40 and 5.41.

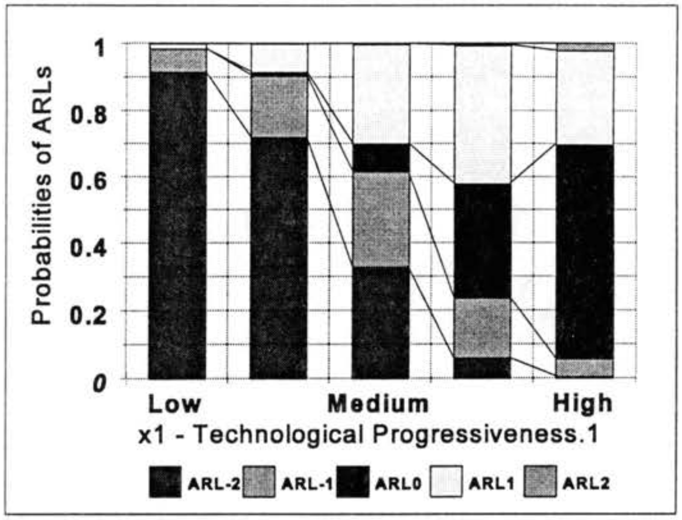

Figure 5.40. Changes in probabilities in ARLs caused by changes in technical progressiveness.1 (soft technologies)

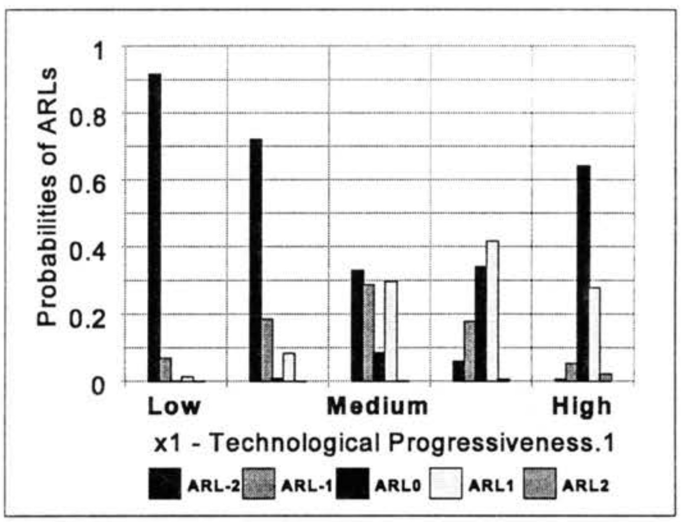

Figure 5.41. Soft technologies: significant effects of technical progressiveness.1 (0 vs -2; 1 vs -2; 2 vs -2; -1 vs 0; -1 vs 2; 1 vs 0).

The overall trend for probabilities of ARLs of -2 and -1 to decrease as technological progressiveness .1 increases does not support Hypothesis 12. In fact, the effects of ARL -2 versus ARL 0, ARL -2 versus ARL 1, ARL -2 versus ARL 2 and to a lesser extent, ARL -1 versus ARL 0 and ARL -1 versus ARL 2 give strong support to the opposite of the hypothesis. The only evidence supporting Hypothesis 12 occurs when looking at the probability of an ARL of 1 versus an ARL of 0 when the level of technological progressiveness.1 increases from medium-high to high. Since the factor does appear to impact all the resistance levels and it appears to be significant in the analysis of variance, technical progressiveness.1 appears to help differentiate between adopters and rejecters of soft technologies.

Technological progressiveness.2 indicates the number of trade shows a firm has attended in the past year and is an alternative measure of technological progressiveness. It was expected that as the number of trade shows increases, adoption resistance decreases (Hypothesis 12). Technological progressiveness.2 appears to be significant with respect to three levels of adoption resistance: adoption versus neutral ($p = .0736$) and leaning to adoption versus neutral ($p = .0657$). The probabilities of all five adoption resistance levels are given in Figure 5.42 and the significant effects are given in Figure 5.43.

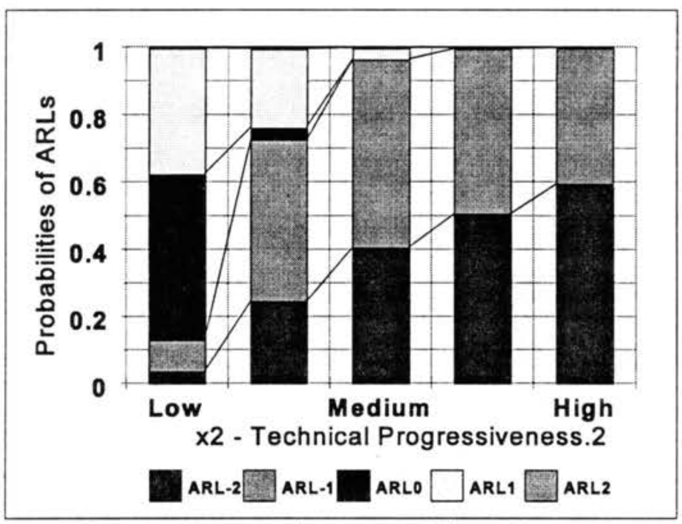

Figure 5.42. Changes in probabilities of ARLs caused by changes in technical progressiveness.2 (soft technologies).

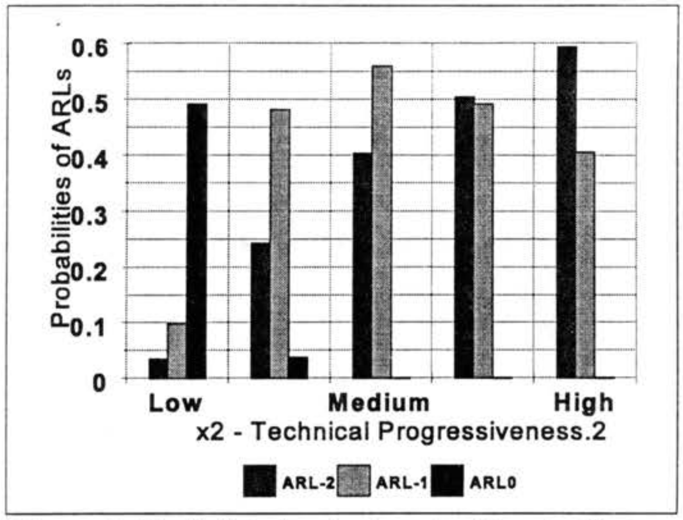

Figure 5.43. Soft technologies: significant effects of changes in technical progressiveness.2 (-2 vs 0, -1 vs 0).

Both effects demonstrate support for the hypothesis up to the point of neutrality. As technical progressiveness.2 increases, the probabilities of ARLs of -2 and -1 increase relative to the probability of an ARL of 0.

Satisfaction with past experiences is significant with respect to four levels of adoption resistance. It was hypothesized that the more favorable a firm's past experiences with new technologies, the lower the adoption resistance would be (Hypothesis 13). Past experiences has significant effects for the following probabilities: adoption versus neutral ($p = .0643$), adoption versus leaning to rejection ($p = .0971$), leaning to adoption versus neutral ($p = .0641$), and leaning to adoption versus leaning to rejection ($p = .0898$) (Figures 5.44 and 5.45). As satisfaction increases, the probabilities of ARLs of -2 or -1 increase and the probabilities of ARLs of 0 or 1 decrease. Therefore, the hypothesis (Hypothesis 13) is supported.

Satisfaction with past experiences produces four significant effects spanning four levels of adoption resistance. This suggests that satisfaction with past experiences differentiates among adoption resistance levels. Since this variable does not appear to produce significant effects in the analysis of variance, it appears that the contribution satisfaction with past experience makes towards explaining variance in adoption resistance levels is minor compared to that of some of the other factors.

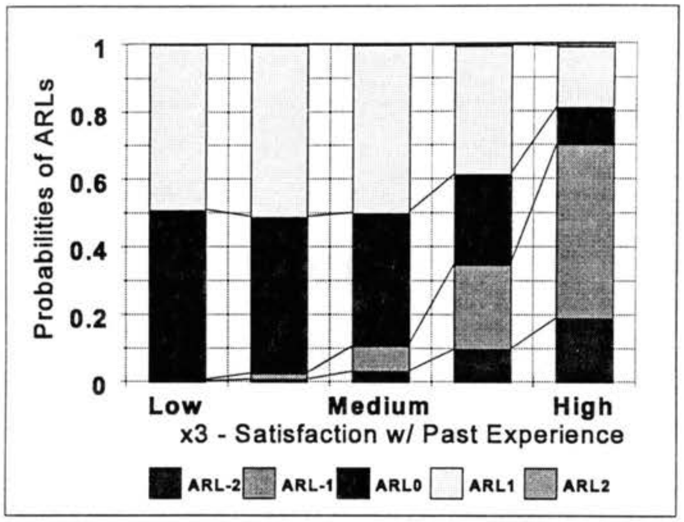

Figure 5.44. Changes in probabilities of ARLs caused by changes in satisfaction with past experience (soft technologies).

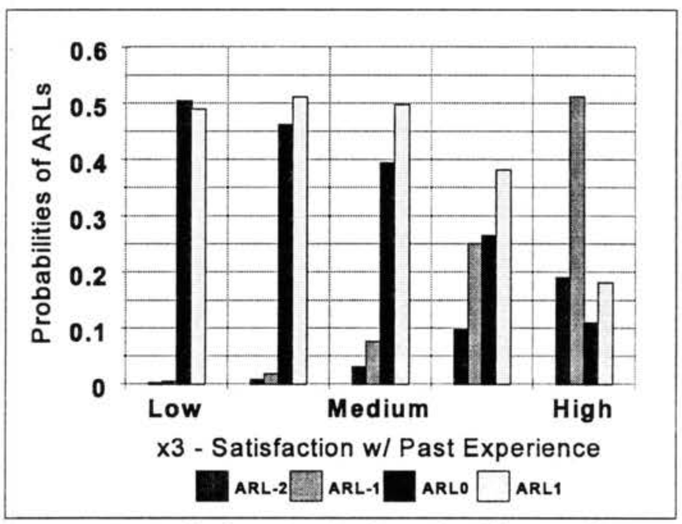

Figure 5.45. Soft technologies: significant effects of past experience on probabilities of ARLs (-2 vs 0, -2 vs 1, -1 vs 0, -1 vs 1).

Firm size, as measured by number of employees, produces only one significant effect: the probability of leaning to rejection versus neutral. It was hypothesized that smaller firm size would be associated with higher adoption resistance (Hypothesis 15). According to the coefficients of the effect, as firm size increases, the probability of an ARL of 1 decreases relative to the probability of an ARL of 0. Confirmation of this is provided in Figure 5.46 and the hypothesis is mildly supported.

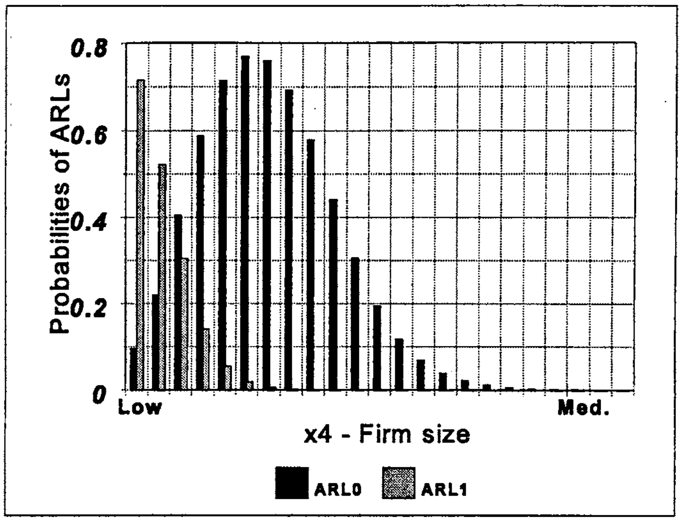

Figure 5.46. Soft technologies: significant effects of changes in firm size on probabilities of ARLs (0 vs 1).

Technical expertise (number of engineers) appears to be significant for the adoption resistance levels of adoption, leaning to adoption, neutral, and leaning to rejection. The significant effects all occur when the comparison involves the neutral position. Changes in probabilities caused by varying the number of engineers are shown in Figures 5.47 and 5.48.

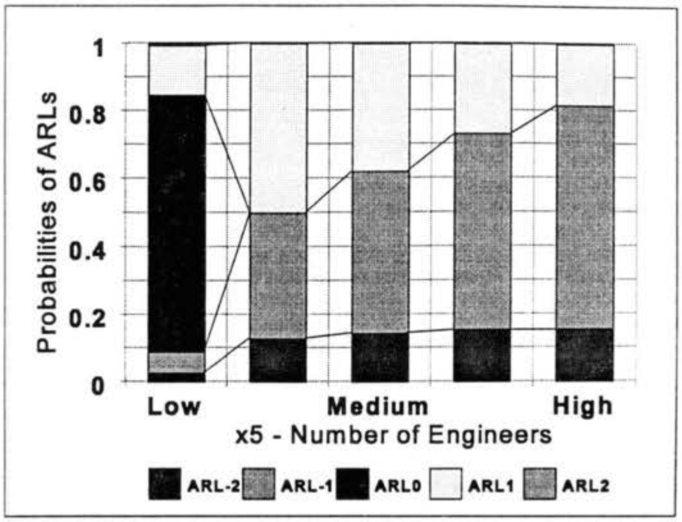

Figure 5.47. Changes in probabilities caused by changes in the number of engineers (soft technologies).

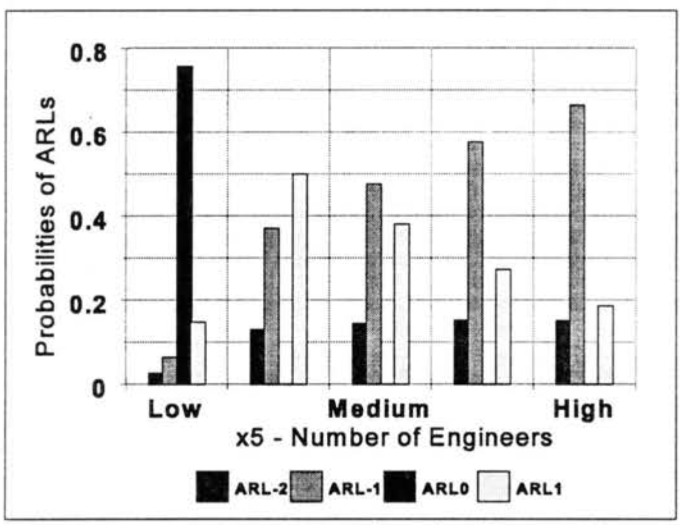

Figure 5.48. Soft technologies: significant effects of number of engineers on probabilities of ARLs (-2 vs 0, -1 vs 0, 0 vs 1).

The effects of ARL -2 versus ARL 0 and ARL -1 versus ARL 0 provide support for the hypothesis that lower technical expertise is associated with higher adoption resistance (Hypothesis 16). Overall, the changes in probability, as seen in Figure 5.47, indicate support for Hypothesis 16. Although, the changes in probability appear to be consistent across the continuum from an ARL of -2 to an ARL of 0, the positive coefficient associated with ARL 1 versus ARL 0, indicates that the hypothesis is not fully supported. Yet, the three effects span four levels of adoption resistance, and seem, to a minor extent, differentiate among adoption resistance levels. Changes in technical expertise (number of engineers) do not trigger significant effects spanning levels on either side of the neutral position. This is compounded by the fact that the coefficient associated with a change in the probability of leaning to rejection versus the probability of neutrality is positive. It does appear as though an increase in the number of engineers a firm employs decreases the probability of a neutral position significantly.

Incommunicability was hypothesized to be positively associated with adoption resistance (i.e. higher incommunicability leads to higher adoption resistance - Hypothesis 7). Significance of this factor is indicated with respect to every level of adoption resistance at least once. The effects are triggered at adoption versus neutral, leaning to adoption versus neutral, neutral versus leaning to rejection and rejection versus adoption. Changes in probabilities are shown in Figures 5.49 and 5.50.

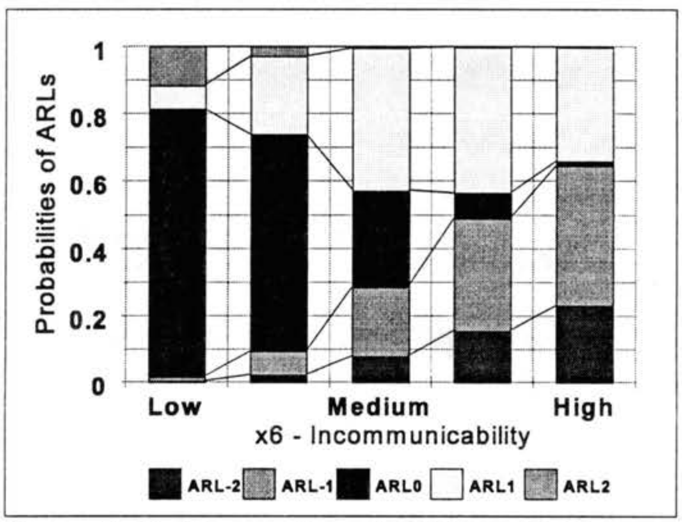

Figure 5.49. Changes in probabilities of ARLs caused by changes in incommunicability (soft technologies).

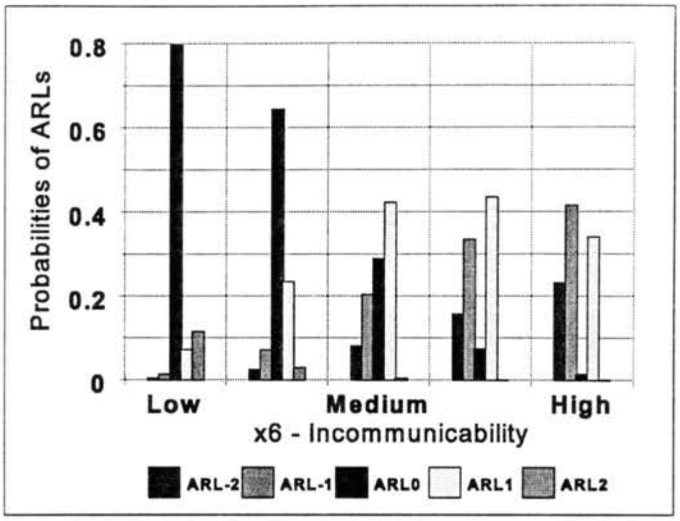

Figure 5.50. Soft technologies: significant effects of changes in incommunicability on the probabilities of ARLs (-2 vs 0, -1 vs 0, 0 vs 1, -2 vs 2).

As incommunicability increases, the probabilities of an ARL of -2 or -1 increase and the probability of a neutral position decreases. Also, the probability of rejection decreases while the probability of adoption increases. These are significant effects in the opposite direction from that hypothesized! As incommunicability increases, the probability of leaning to rejection increases relative to the probability of a neutral position. This is the only support indicated for Hypothesis 7. The preponderance of evidence suggests that an increase in incommunicability leads to an increase in the likelihood of a lower adoption resistance level, and that incommunicability is likely to differentiate among levels of adoption resistance. In addition, incommunicability is nearly significant ($\alpha = .10$) in the analysis of variance.

Higher levels of non-trialability were hypothesized to lead to higher levels of adoption resistance (Hypothesis 3). Non-trialability produces three significant effects when benchmarked on the rejection level: ARL -2 versus ARL 2 (p = .0392), ARL -1 versus ARL 2 (p = .0237), and ARL 1 versus ARL 2 (p = .0480) . The sets of probabilities that were affected by a change in non-trialability were leaning to rejection, adoption and leaning to adoption each relative to the probability of rejection. Changes in probabilities are shown in Figures 5.51 and 5.52.

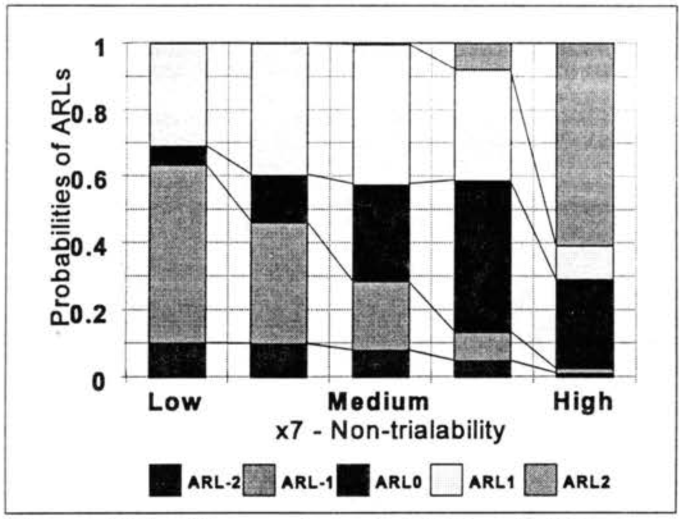

Figure 5.51. Changes in probabilities of ARLs caused by changes in non-trialability (soft technologies).

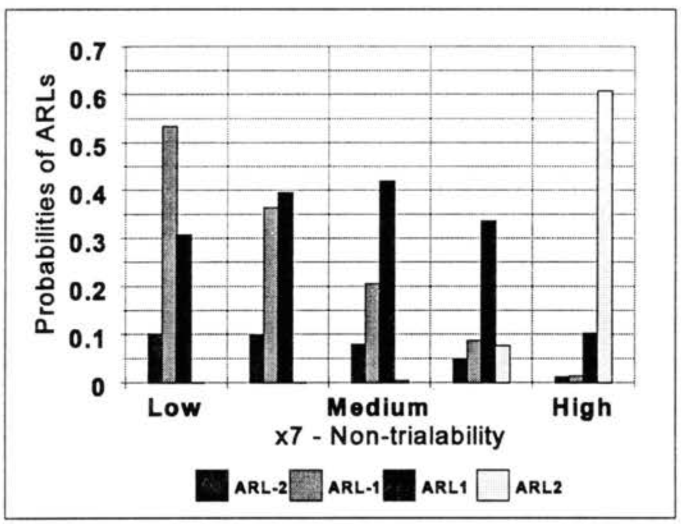

Figure 5.52. Soft technologies: significant effects on probabilities of ARLs caused by changes in non-trialability (-2 vs 2, -1 vs 2, 1 vs 2).

In every case, the probability of a lower ARL (-2, -1 or 1) decreases as the probability of rejection increases. Therefore, there is support for Hypothesis 3. Also, since the effects span the continuum and specifically involve four levels of adoption resistance, it appears that non-trialability may differentiate between adopters and rejecters. However, the contribution of this variable in explaining variance of adoption resistance levels appears to be eclipsed by the contributions of other factors.

Discontinuity was expected to be positively associated with adoption resistance (Hypothesis 2). The only significant effect produced by discontinuity is that relating the probabilities of adoption and leaning to rejection. As discontinuity increases, the probability of an ARL of 1 increases relative to the probability of an ARL of -2 (Figure 5.53). Thus, there appears to be support for the hypothesis up to the point of leaning to rejection.

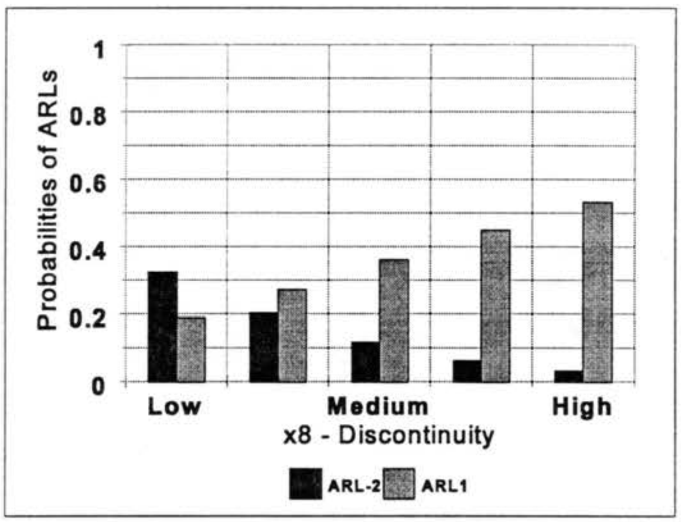

Figure 5.53. Soft technologies: significant effects of changes in discontinuity on the probabilities of ARLs (-2 v 1).

The remaining five variables triggered significance with respect to all five adoption resistance levels. Therefore, they are each considered to be likely to differentiate among adoption resistance levels. Since the analysis proceeds in the same manner, only the graphs for each variable and a very brief description of the interpretation of the effect with respect to its respective hypothesis will be presented.

There is overwhelming support for the hypothesis that higher incompatibility is associated with higher adoption resistance (Hypothesis 1) (Figures 5.54 and 5.45). All effects support Hypothesis 1. In addition, since the factor appears to be significant in the analysis of variance (p = .0025), it is concluded that incompatibility helps differentiate between adopters and rejecters when considering soft technologies.

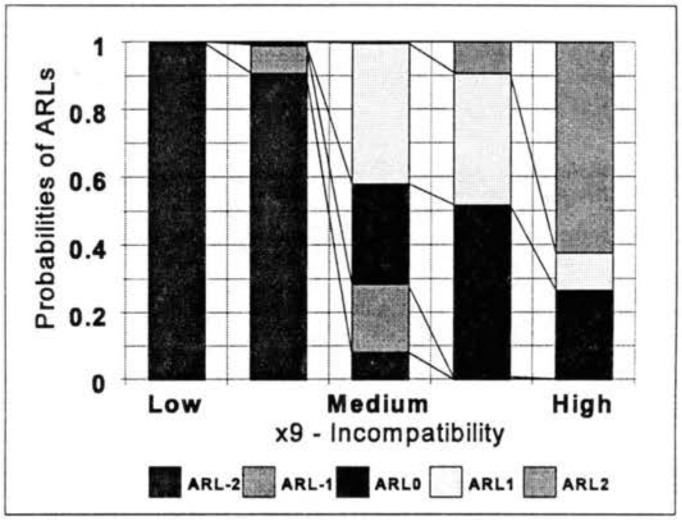

Figure 5.54. Changes in probabilities caused by changes in incompatibility (soft technologies).

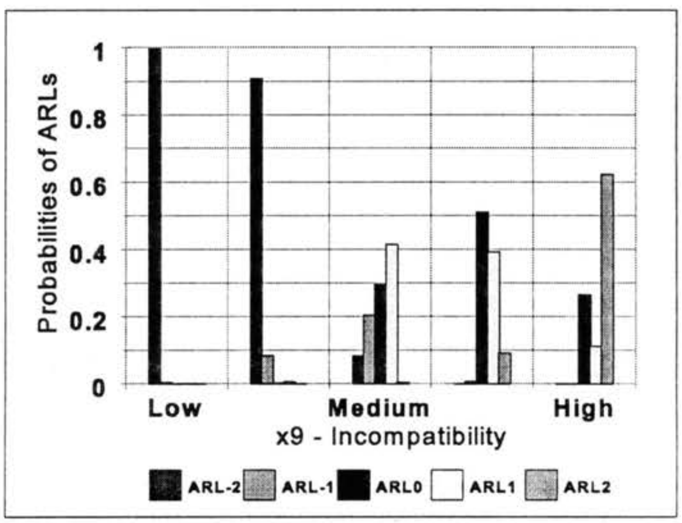

Figure 5.55. Soft technologies: significant effects of incompatibility on the probabilities of ARLs (-2 vs -1, -2 vs 0, -2 vs 1, -2 vs 2, -1 vs 0, -1 vs 1, -1 vs 2, 1 vs 2).

Hypothesis 11 suggested that the higher the irreversibility of a technology, the higher the adoption resistance. As can be seen in Figures 5.56 and 5.57, increased irreversibility appears to result in higher probabilities of all adoption resistance levels except the neutral position. It seems that increased irreversibility results in a reduced likelihood of being neutral in the technology adoption/rejection decision (when considering soft technologies). Since increases in the probabilities of ARLs of 1 and 2 occur as irreversibility increases, there is some support for Hypothesis 11 beginning at the point of neutrality. This variable does appear to be significant in the analysis of variance (p = .0176), so it appears to differentiate adopters from rejecters. However, given the inconsistent support for they hypothesis, it does not appear that the effect of irreversibility can be described monotonically.

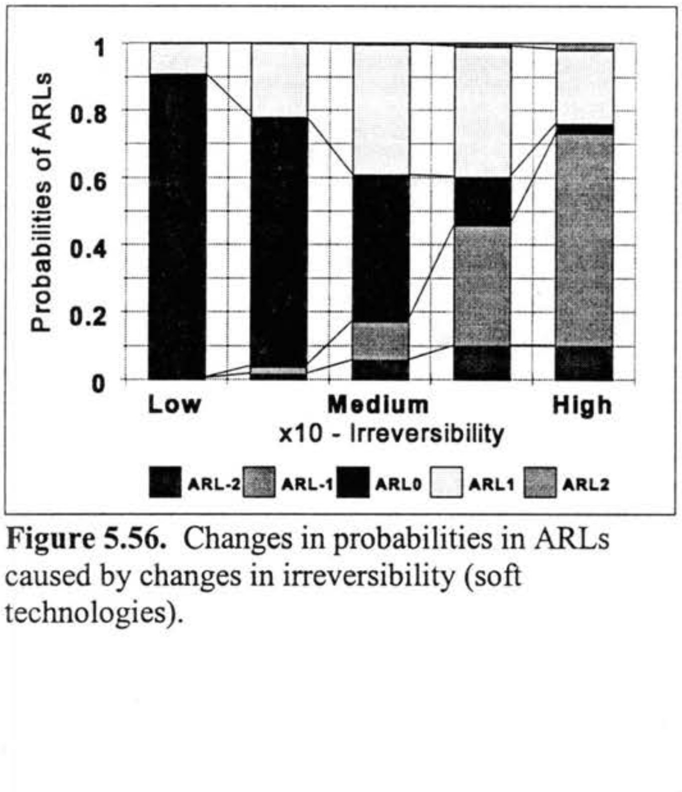

Figure 5.56. Changes in probabilities in ARLs caused by changes in irreversibility (soft technologies).

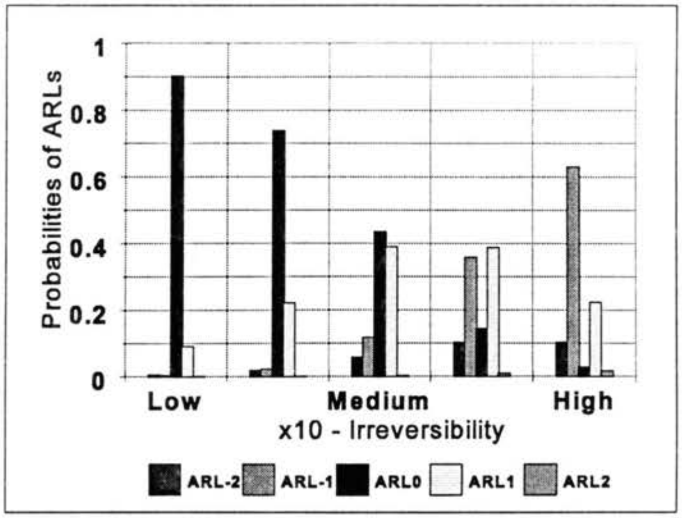

Figure 5.57. Soft technologies: significant effects of irreversibility on the probability of ARLs (-2 vs 0, -1 vs 0, 1 vs 0 , 2 vs 0).

Time to implementation was hypothesized to have a positive effect on adoption resistance, i.e. the longer the time to implementation, the higher the adoption resistance (Hypothesis 8). Time to implementation appears to be significant in the analysis of variance (p = .0894), but the question of whether or not its effect supports Hypothesis 8 remains. Since time to implementation produces significant effects with respect to all levels of adoption resistance at least once, Figure 5.58 gives a good overview of the effect of time to implementation. It appears as though longer implementation times increase the likelihood of ARLs of -1 or 0. When looking at the significant effects (Figure 5.59), it becomes apparent that the effect triggered at adoption versus leaning to adoption supports the hypothesis. There is also some minor support for the hypothesis indicated by the significant effect at leaning to rejection versus rejection. However, the effects at leaning to adoption versus leaning to rejection, and neutral versus leaning to rejection provide strong support in the opposite direction. The opposite direction of impact that the variable appears to have towards the extremes of the continuum suggests that the effect is not monotonic.

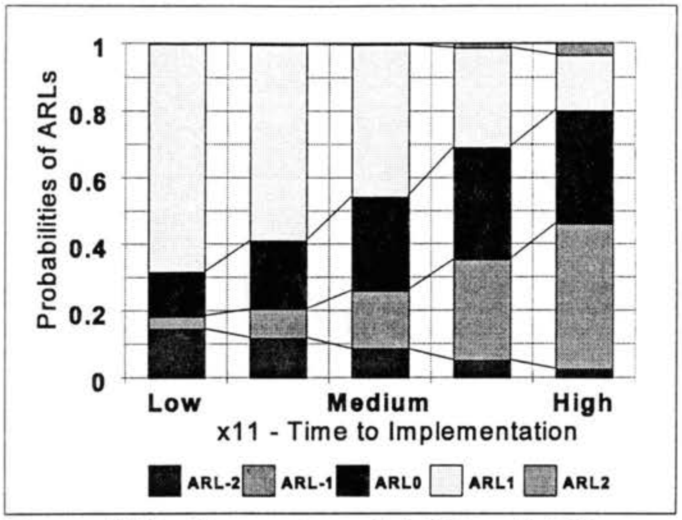

Figure 5.58. Changes in probabilities of ARLs caused by changes in time to implementation (soft technologies).

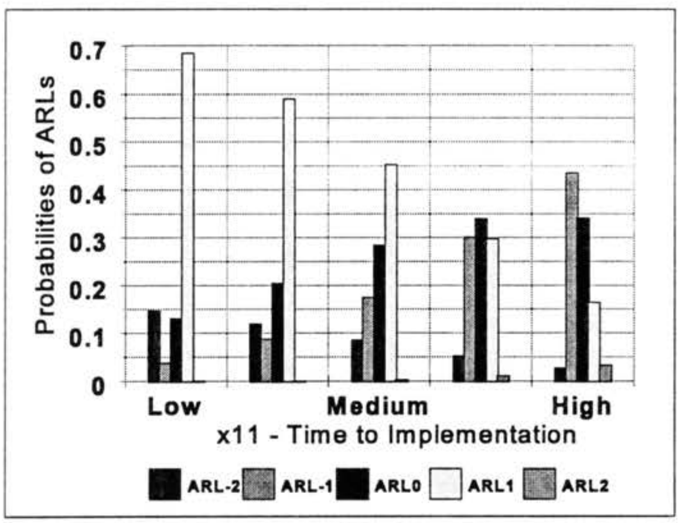

Figure 5.59. Soft technologies: significant effects of time to implementation on probabilities of ARLs (-2 vs -1, -1 vs 1, 0 vs 1, 1 vs 2).

Increased time to realization of benefits was also expected to lead to higher levels of adoption resistance (Hypothesis 9). As can be seen in Figure 5.60, the data provide strong support for this hypothesis. Each effect that tested significant appears to support the hypothesis (Figure 5.61). Furthermore, time to realization was significant in the analysis of variance (p = .0490), indicating that the firm's perception of the time to realization may help differentiate between levels of adoption resistance (i.e., may help differentiate between adopters and rejecters).

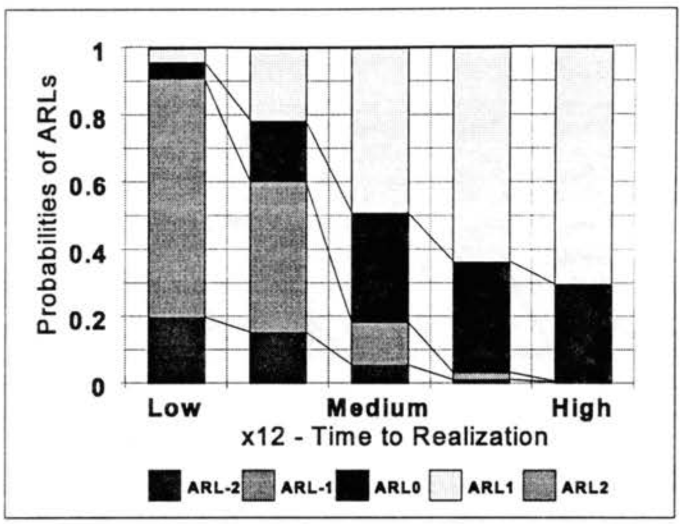

Figure 5.60. Changes in probabilities of ARLs caused by changes in time to realization (soft technologies).

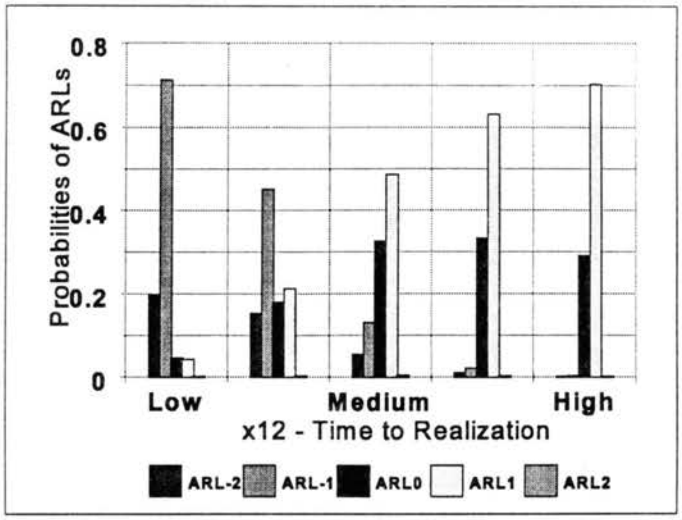

Figure 5.61. Soft technologies: significant effects of time to realization on probabilities of ARLs (-2 vs 0, -2 vs 1, -1 vs 0, -1 vs 1, -1 vs 2).

Hypothesis 20 suggested that the more difficult it is to modify a technology, the higher the adoption resistance would be. Figures 5.62 and 5.63 demonstrate that the data strongly support this hypothesis. As difficulty increases, the probabilities of ARLs of 1 or 2 both increase and probabilities of ARLs of -1 or -2 both decrease. The probability of a neutral position increases up to the medium level of difficulty, then it decreases. This shows strong support for the hypothesis. In addition, the variable appears to be significant in the analysis of variance (p = .0406) and thus, it appears to differentiate between adopters and rejecters.

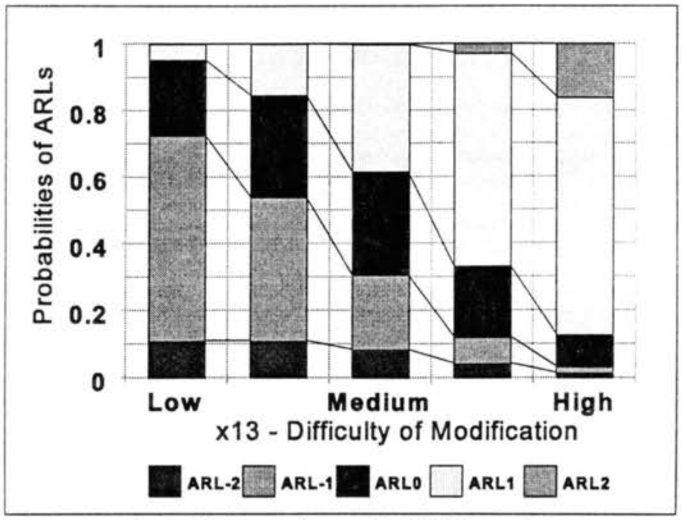

Figure 5.62. Changes in probabilities of ARLs caused by changes in difficulty of modification (soft technologies).

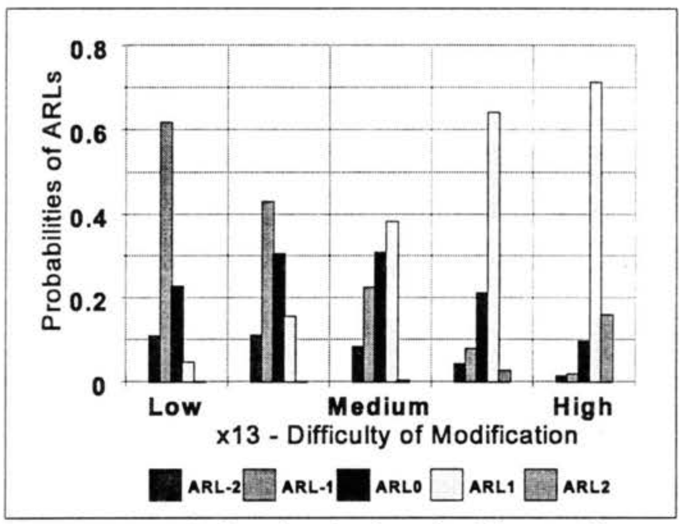

Figure 5.63. Soft technologies: significant effects of difficulty of modification on probabilities of ARLs (-2 vs 1, -2 vs 2, -1 vs 1, -1 vs 2, 0 vs 1, 0 vs 2).

It was expected that technologies that could be implemented in stages would meet less adoption resistance than those that could not be implemented in stages (Hypothesis 4). However, the soft technology data did not support this hypothesis. As can be seen in Figures 5.64 and 5.65, as indivisibility increases, the likelihood of ARLs of -2 or -1 both increase!

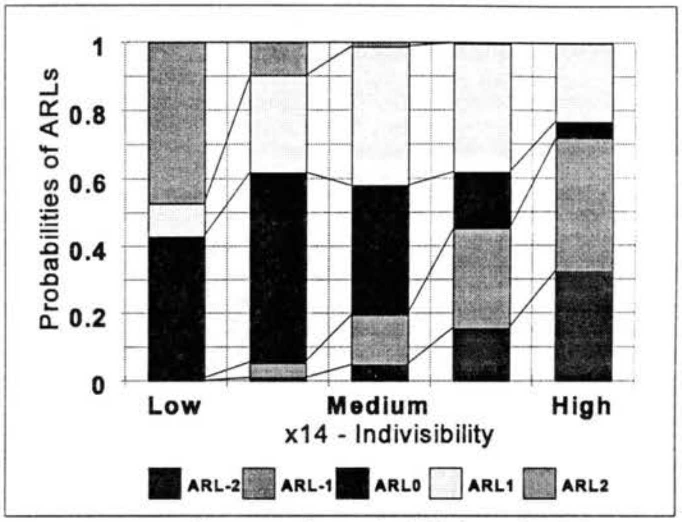

Figure 5.64. Changes in probabilities of ARLs caused by changes in indivisibility (soft technologies).

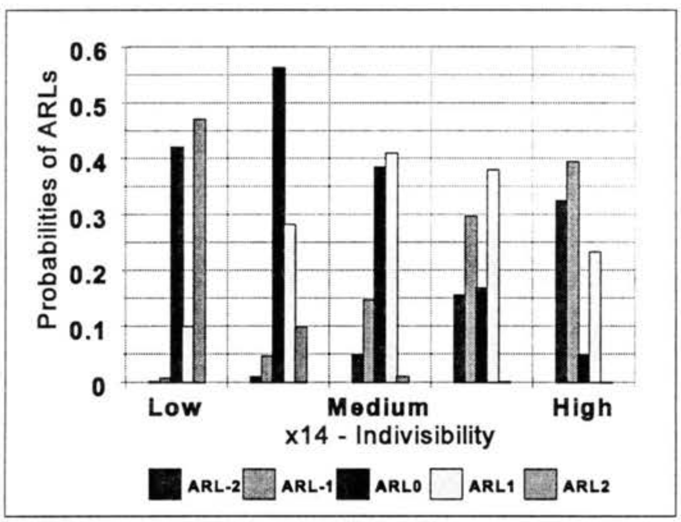

Figure 5.65. Soft technologies: significant effects of indivisibility on probabilities of ARLs (-2 vs 0, -2 vs 2, -1 vs 0, -1 vs 2, 1 vs 2, and 0 vs 2).

None of the significant effects support the hypothesis. For example, as indivisibility increases, the probability of an ARL of -2 increases and the probability of an ARL of 0 decreases; the probability of an ARL of -2 increases and the probability of an ARL of 2 decreases; the probability of an ARL of -1 increases and the probabilities of an ARL of 0 or 2 both decrease. Since indivisibility is significant in the analysis of variance (p = .0535), it appears that indivisibility can help differentiate between adopters and rejecters, but that its effect is opposite from what was hypothesized.

5.5.2.1. Summary of results for soft technologies, all effects

All fourteen factors appear to have significant effects on the probabilities of at least two adoption resistance levels when considering the adoption resistance levels two at a time for soft technologies. The spans of these effects are summarized in Table 5.18. The variables with the largest and most consistent impacts are incompatibility, difficulty of modification, and indivisibility. These are also significant factors in the analysis of variance. In decreasing order of significance, the variables that are significant in the analysis of variance (the "major players") are incompatibility, technical progressiveness.1, irreversibility, difficulty of modification, time to realization, indivisibility, and time to implementation. Of these seven variables, technical progressiveness.1 is the only characteristic; the other six variables are risk factors.

Table 5.18. Spans of significant effects in the soft technologies model

	Expected Direction (found expected effect as stated in hypothesis)				Unexpected Direction (found the opposite effect from that hypothesized)			
	Spans 2 ARLs	Spans 3 ARLs	Spans 4 ARLs	Spans 5 ARLs	Spans 2 ARLs	Spans 3 ARLs	Spans 4 ARLs	Spans 5 ARLs
Technical progressiveness.1	(-1 v 0)	(-2 v 0)	(-2 v 1) (-1 v 2)	(-2 v 2)		(0 v 2)		
Technical progressiveness.2	(-1 v 0)	(-2 v 0)						
Past experience	(-1 v 0)	(-2 v 0) (-1 v 1)	(-2 v 1)					
Firm size	(0 v 1)							
Technical expertise	(-1 v 0)	(-2 v 0)			(1 v 0)			
Incommunicability	(1 v 0)				(-1 v 0)	(0 v -2)		(-2 v 2)
Non-trialability	(1 v 2)		(-1 v 2)	(-2 v 2)				
Discontinuity			(-2 v 1)					
Incompatibility	(1 v 2) (-1 v 0) (-2 v -1)	(-2 v 0) (-1 v 1)	(1 v -2) (-1 v 2)	(-2 v 2)				
Irreversibility	(0 v 1)	(0 v 2)			(-1 v 0)	(-2 v 0)		
Time to Implement	(1 v 2) (-2 v -1)				(1 v 0)	(-1 v 1)		
Time to Realization	(-1 v 0)	(-2 v 0) (-1 v 1)	(-2 v 1) (-1 v 2)					
Difficulty of Modification	(1 v 0)	(1 v -1) (2 v 0)	(1 v -2) (-2 v 1)	(-2 v 2)				
Indivisibility					(-1 v 0) (1 v 2)	(0 v 2) (-2 v 0)	(-1 v 2)	(-2 v 2)

Incompatibility produces eight significant effects, all supporting the hypothesis that the higher the perceived incompatibility of the technology, the higher the adoption resistance (Hypothesis 1). The effects span the continuum from adoption to rejection and appear to differentiate between adopters and rejecters of the three soft technologies of this research. As discussed earlier, incompatibility was a combination of three sub-factors: how well a technology fit into the current production system, how much training was required to implement the technology and how much support upper management gave to the adoption of the technology. Therefore, it appears that soft technology developers can take several steps to reduce incompatibility and thereby expect a decrease in adoption resistance. As discussed earlier, soft technology developers can provide on-site training with the purchase/acquisition of the technology. Second, technology developers can improve efforts to convey the soft technology's advantages to the upper management of a firm and gain management's support for the technology. Third, soft technology developers can increase (when possible) the options available with a technology that make it easier to fit into a particular production line.

Technical progressiveness.1 produces five significant effects supporting the hypothesis that lower technical progressiveness is associated with higher adoption resistance (Hypothesis 12). It appears to differentiate between levels of adoption resistance even though it also produces one significant effect in the opposite direction of the hypothesis. The preponderance of evidence suggests that Hypothesis 12 is well supported. Therefore, soft technology developers might target firms that are perceived as technically progressive in order to increase the likelihood of adoption and reduce the likelihood of rejection. Technical progressiveness is a characteristic of the firm and it is not easy for technology developers to change a firm's characteristics. However, soft technology developers might be able to reduce adoption resistance by providing incentives for manufacturers to attend trade shows, thereby increasing technical progressiveness.2. The problem with this strategy is that since this is not necessarily technology-related, the result may be an increased likelihood in adopting a competitor's technology.

Irreversibility produces a significant effect in the analysis of variance. This indicates that irreversibility helps explain some of the variance in adoption resistance levels. However, the effect does not appear to be uni-directional in its effect along the continuum of adoption resistance levels. The effect supports the hypothesis that higher irreversibility is associated with higher adoption resistance beginning at the point of neutrality. Up to this point, the opposite of the hypothesis is supported. Therefore, irreversibility appears to be a significant but non-monotonic factor in explaining variance in adoption resistance and in differentiating between adopters and rejecters.

Difficulty of modification produces six consistent effects across all five levels of the continuum. These effects support Hypothesis 10 across the continuum; Hypothesis 10 suggested that the more difficult it is to modify a technology, the higher the adoption resistance. If soft technology developers want to reduce adoption resistance, then this set of results suggests that they should look for easier means of modifying the technology to fit into different production systems.

Time to realization produces five consistent effects supporting Hypothesis 9 (the longer the time to realization of benefits, the higher the adoption resistance). The reason this appears to be more important for soft technologies than for hard technologies may be that the benefits from soft technologies may be perceived as more nebulous and more difficult to relate to a monetary impact. The data suggest that developers of soft technologies could either decrease the amount of time to realization of benefits or demonstrate how the benefits can be identified sooner or recognized more easily to reduce adoption resistance

Indivisibility produces six significant effects that are consistent in their support for the opposite of Hypothesis 4 (The higher the indivisibility of the technology, the higher the adoption resistance). These effects span the entire continuum. Since indivisibility is significant in the analysis of variance, it is considered to differentiate among the levels of adoption resistance. The data suggest that one means of reducing adoption resistance to soft technologies may be to increase the difficulty with which a particular technology can be implemented in stages. In other words, that data suggest that adoption resistance is lowest when implementation is an all or nothing endeavor. This may force a stronger commitment to the technology than what would occur if the technology were perceived to be highly divisible. Although the effects of indivisibility of hard technologies does not appear to have a significant impact on the overall model, it is interesting to note that these results (with respect to indivisibility) are completely opposite from the results of the hard technologies analysis.

The last factor to have a significant effect in the analysis of variance of soft technology adoption resistance levels is time to implementation. Time to implementation appears to have two significant effects that support the hypothesis that the longer the implementation time, the higher the adoption resistance. These two effects occur at the extremes of the continuum. Two significant effects supporting the opposite of the hypothesis occur in the middle of the continuum. This suggests that while time to implementation has a significant effect on adoption resistance levels, this effect is not uniform across the continuum.

The variables satisfaction with past experiences, incommunicability, non-trialability, and technical expertise demonstrate an ability to differentiate among adoption resistance leves through relative effects, but they do not appear to be major players in the analysis of variance. Factors that are consistent in their support for their respective hypotheses are technical progressiveness.2, past experience, firm size, non-trialability, incompatibility, time to realization, and difficulty of modification. Indivisibility is the only factor that is consistent in its support for the opposite of its respective hypothesis. Technical progressiveness.2 produces effects only dealing with the adoption side of the continuum and firm size produces only one effect and it deals with the rejection side of the continuum. This may suggest that technical progressiveness.2 explains adoption behavior but not rejection behavior and that firm size explains rejection behavior but not adoption behavior.

5.5.2.2. Goodness-of-fit for the soft technologies model

The number of "correct" classifications were used to assess the goodness-of-fit of the model. The correct classification rates are summarized in Table 5.19.

Table 5.19. Summary of correct classification rates for the soft technologies model.

ARL	Number observed	Number expected	Number correct classifications	Percentage of observations correctly predicted	Percentage of correct predictions
-2	31	31	23	74.19%	74.19%
-1	18	16	10	55.56%	62.50%
0	40	45	31	77.50%	68.89%
1	37	36	25	67.57%	69.44%
2	9	7	7	77.78%	100.00%
Total	135	135	96	71.11%	71.11%

The proportional chance criterion suggests that if the ARLs were assigned randomly, only 25.1% of the classifications would be correct. Therefore, the overall correct classification rate of 71.1% implies that the model fits the data rather well. Also, the likelihood ratio (196.50 with 424 degrees of freedom) tested nonsignificant ($p = 1.00$) and thus, it was concluded that the model fit the data.

5.6 Level 3 - individual technologies

The analysis was conducted for six data sets consisting of the data related to each of the six technologies. There was a major difference in the conducting of this analysis: firms in the adopt and lean to adopt categories were combined into a single category; and firms in the reject and lean to reject categories were combined into a single category. This was done to ensure that there were sufficient responses in each category to allow the completion of the analysis (twenty times one less than the number of outcome categories). Even with this change, some of the technologies did not have a sufficient volume of data to conduct the analysis since survey respondents only answered questions regarding technologies of which they were aware. This was particularly true for the softer technologies with data for statistical process control and pc-based production control being insufficient for further analysis.

5.6.1 Thin saw kerf technology

The multinomial logit model was conducted with three adopter/rejecter outcome categories: adopt reject, and neutral. Since β coefficients were estimated for two response levels, 40 observations were needed in order to be reasonably sure of meaningful analysis. Fifty-two observations were used in this analysis, and the observed outcomes (survey results) are given in Table 5.20.

Table 5.20. Observed levels of adoption resistance (thin saw kerf technology)

Adoption resistance level (response)	Frequency of response
Adoption	12
Neutral	19
Rejection	21
Total	52

The results of the analysis of variance are given in Table 5.21. Three variables produced significant effects at the $\alpha = .10$ level: irreversibility, discontinuity, and technical progressiveness.1.

Table 5.21. Analysis of variance for the thin saw kerf technology model

Source	p-value
Intercept	.9986
Technical progressiveness.1	.0994***
Technical progressiveness.2	.6791
Past experiences	.8654
Firm size	.5677
Technical expertise	.3708
Incommunicability	.1120
Non-trialability	.8036
Discontinuity	.0924***
Incompatibility	.1119
Irreversibility	.0725***
Time to implementation	.1115
Time to realization	.4169
Difficulty of modification	.1809
Indivisibility	.2413

*Significant at $\alpha = .01$ level
**Significant at $\alpha = .05$ level
***Significant at $\alpha = .10$ level

The results of the multinomial logit analysis when benchmarking on neutral are given in Table 5.22. Six variables appear to be significant at the $\alpha = .10$ level: technical progressiveness.1, incommunicability, discontinuity, incompatibility, irreversibility, and indivisibility. Two other factors produce significant effects only at ARL 1 versus ARL versus -1; those variables are time to implementation ($p = .0385$) and difficulty of modification ($p = .0650$).

Table 5.22. Logit analysis of factors affecting the probability of thin saw kerf technology adoption resistance level when benchmarking on neutral.

	Adopt (j = -1)		Reject (j = 1)	
	estimate	p-value	estimate	p-value
β_{0j} Intercept	-1.5256	.9633	-1.3668	.9646
β_{1j} Technical progressiveness.1	.7001	.8176	-9.7583	.0402**
β_{2j} Technical progressiveness.2	-21.8121	.3818	-5.6307	.7238
β_{3j} Past experiences	-1.7547	.7072	-1.3551	.6218
β_{4j} Firm size	-12.4658	.7532	-40.3740	.2900
β_{5j} Technical expertise	35.6650	.3867	43.6891	.1597
β_{6j} Incommunicability	-14.5669	.0396**	-8.2062	.0740***
β_{7j} Non-trialability	-.2794	.9350	-2.7648	.5148
β_{8j} Discontinuity	-4.6558	.0945***	-4.5392	.0501***
β_{9j} Incompatibility	1.3537	.7061	14.4415	.0364**
β_{10j} Irreversibility	4.7938	.3273	13.7605	.0276**
β_{11j} Time to implement	3.5036	.1193	-4.4410	.1368
β_{12j} Time to realization	-1.1325	.6828	-3.8082	.1864
β_{13j} Difficulty of modification	-3.0031	.3214	2.8868	.3057
β_{14j} Irreversibility	.2979	.9348	5.7945	.0989***

** indicates significance at the $\alpha = .05$ level
*** indicates significance at the $\alpha = .10$ level

The multinomial logit model was also run with the adoption and rejection level outcomes as the benchmarks. Coefficients and p-values are given in Appendix I.

Technical progressiveness.1 produces two significant effects: ARL -1 versus ARL 1 (10.4584, p = .0413) and ARL 0 versus ARL 1 (9.7583, p = .0402). The positive coefficients associated with both effects when benchmarking on the rejection level (ARL = 1), suggest that as the measure technical progressiveness.1 increases, the log odds of rejection versus each of the other two possible outcomes is reduced (Figure 5.66). Therefore, it appears that higher technical progressiveness is associated with lower adoption resistance and Hypothesis 12 is supported. Also, the two effects span the reduced continuum and therefore, it seems likely that technical progressiveness.1 helps differentiate among adopters, rejecters and neutrals (undecideds). This is confirmed in the analysis of variance.

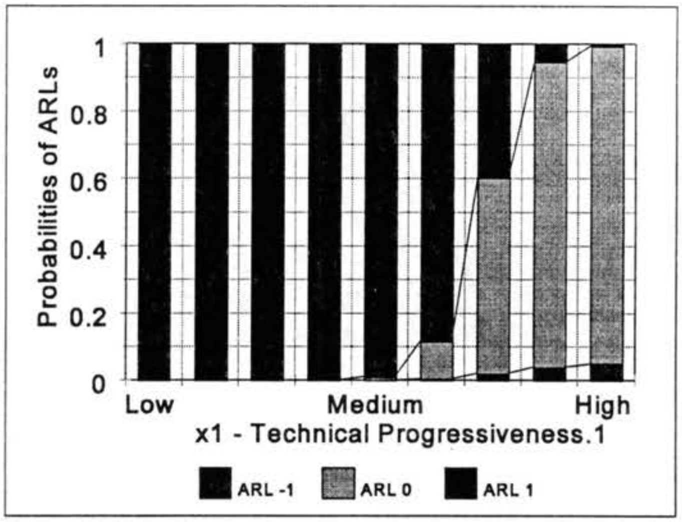

Figure 5.66. Thin saw kerf technology: effects of technical progressiveness.1 on probabilities of ARLs (-1 vs 1, 0 vs 1).

Incommunicability produces significant effects when benchmarked on the neutral position. The effect has negative coefficients for both adoption and rejection indicating that as incommunicability increases the probability of a neutral position increases (Figure 5.67). As can be seen in Figure 5.67, the hypothesis that higher incommunicability is associated with higher adoption resistance is somewhat supported up to the medium level of incommunicability, then the opposite of the hypothesis appears to be the case. Therefore, there is some support for Hypothesis 7, but the hypothesis is not fully supported. Since the two effects cover the reduced continuum and involve all three adoption resistance levels, it seems likely that incommunicability differentiates among resistance levels. Incommunicability is nearly significant in the analysis of variance, suggesting that its ability to differentiate among resistance levels is only slightly outweighed by some other factors' differentiating abilities.

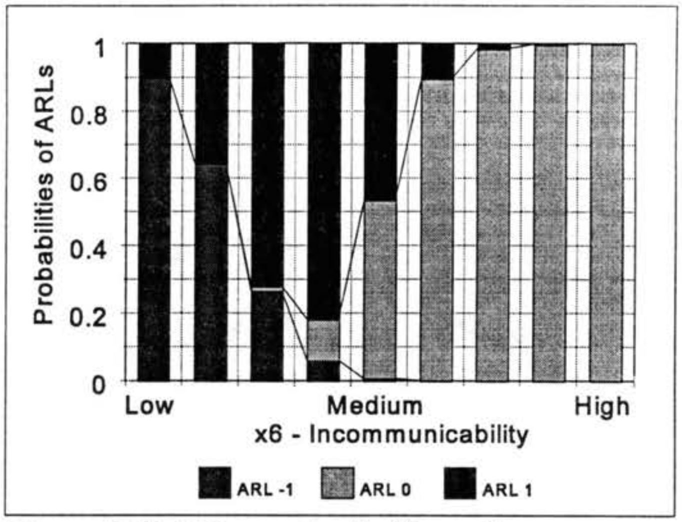

Figure 5.67. Thin saw kerf: effects of incommunicability on probabilities of ARLs (-1 vs 0, 1 vs 0).

Discontinuity also produces two significant effects when benchmarking on the neutral position. The coefficients are both negative and nearly equal in magnitude. It appears that an increase in discontinuity is associated with a higher probability of a neutral position when considering the adoption of thin saw kerf technology. As can be seen in Figure 5.68, there is some very minor support for the hypothesis that higher discontinuity is associated with higher adoption resistance but only to the point of neutrality. This support is attributable to the negative coefficient of the effect at ARL -1 versus ARL 0 ($p = .0945$). Since discontinuity produces a significant effect in the analysis of variance, the factor does appear to differentiate between rejecters and adopters. However, the effect is not consistent throughout the continuum.

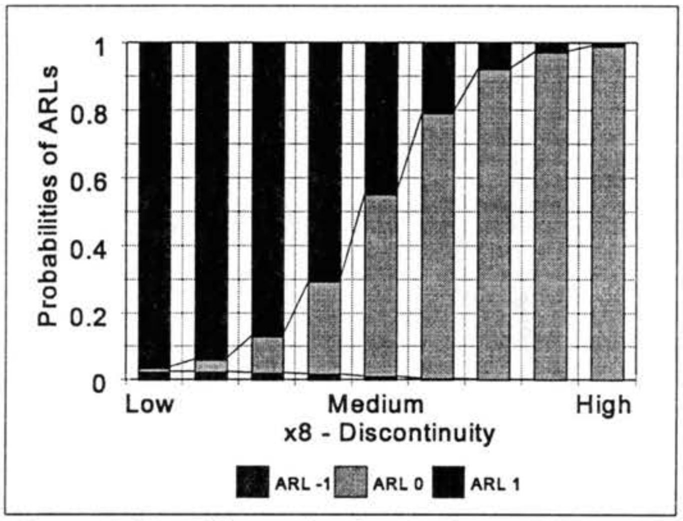

Figure 5.68. Thin saw kerf technology: effects of discontinuity on probabilities of ARLs (-1 vs 0, 1 vs 0).

Incompatibility produces significant effects at ARL 0 versus ARL 1 ($p = .0364$) and ARL -1 versus ARL 1 ($p = .0715$). When benchmarking on ARL 1, the coefficients of both ARL -1 and ARL 0 comparisons are negative (Figure 5.69). This implies that as incompatibility increases, the likelihood of rejection increases. This gives support for the hypothesis that as incompatibility increases, adoption resistance increases (Hypothesis 1). Incompatibility demonstrates an ability to differentiate among adoption resistance levels, but it is not a major player in the analysis of variance.

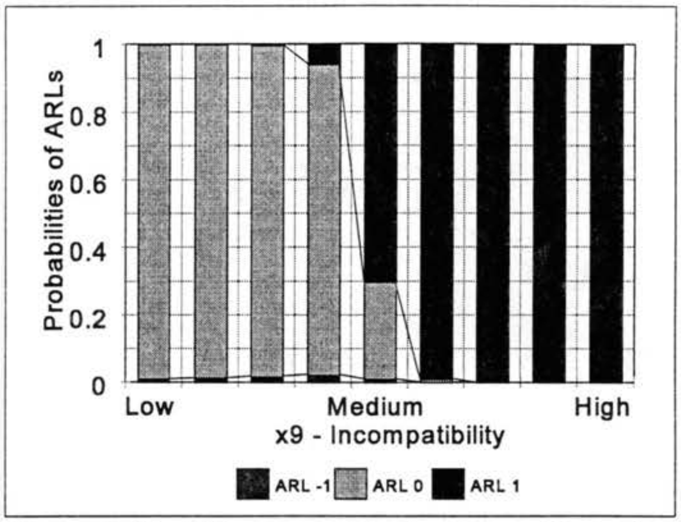

Figure 5.69. Thin saw kerf technology: effects of incompatibility on probabilities of ARLs (-1 vs 1, 0 vs 1).

Irreversibility produces significant effects at ARL 1 versus ARL 0 (p = .0276), and at ARL 1 versus ARL -1 (p = .0597). When benchmarked on rejection (ARL 1), both effects have negative coefficients, implying that as irreversibility increases, adoption resistance increases (confirmed in Figure 5.70). Therefore, it appears that there is support for the hypothesis that higher irreversibility leads to higher adoption resistance (Hypothesis 11). The effects span the reduced continuum, and it appears that this factor differentiates between adopters and rejecters since irreversibility produces a significant effect in the analysis of variance.

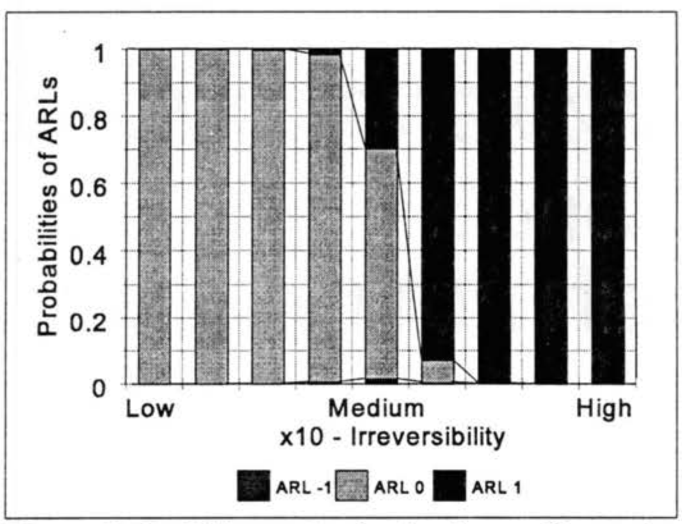

Figure 5.70. Thin saw kerf technology: effects of irreversibility on probabilities of ARLs (-1 vs 1, 0 vs 1).

Time to implementation was expected to be positively related to adoption resistance. A significant effect was detected at ARL -1 versus ARL 1. The positive coefficient obtained when benchmarked on rejection implies that as time to implementation increased, the log odds of an ARL of -1 increases versus an ARL of 1 (Figure 5.71). This is opposite from what was expected per Hypothesis 8 (The longer the time to implementation of a technology, the higher the adoption resistance). The one effect spans the continuum without specifically involving the neutral position, so it seems reasonable to expect time to implementation to differentiate between adopters and rejecters. In addition, the factor is nearly significant in the analysis of variance.

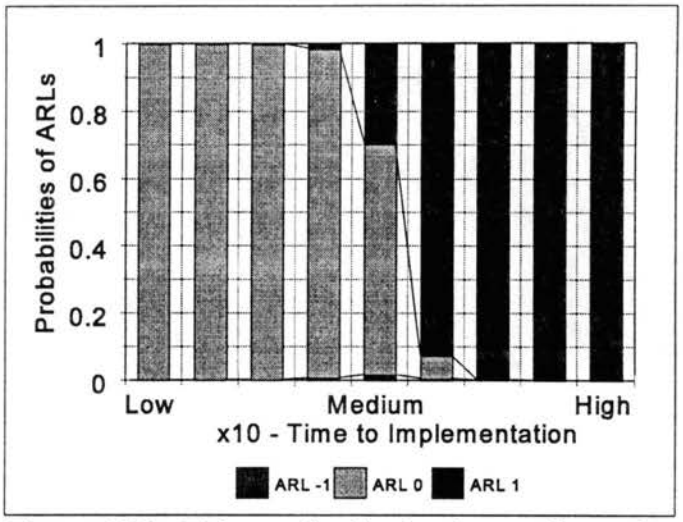

Figure 5.71. Thin saw kerf technology: effects of time to implementation on probabilities of ARLs (-1 vs 1).

A negative, significant effect is produced by difficulty of modification at ARL -1 versus ARL 1 ($p = .0650$). Therefore, as difficulty of modification increases, the probability of adoption decreases relative to the probability of rejection. This is confirmed in Figure 5.72. This factor appears to lend support to Hypothesis 10 (the more difficult it is to modify a technology, the higher the adoption resistance). Difficulty of modification appears to possess some differentiating ability since its one effect spans the continuum. The factor, however, appears to be dwarfed in its ability to explain variance in adoption resistance levels when compared to other factors.

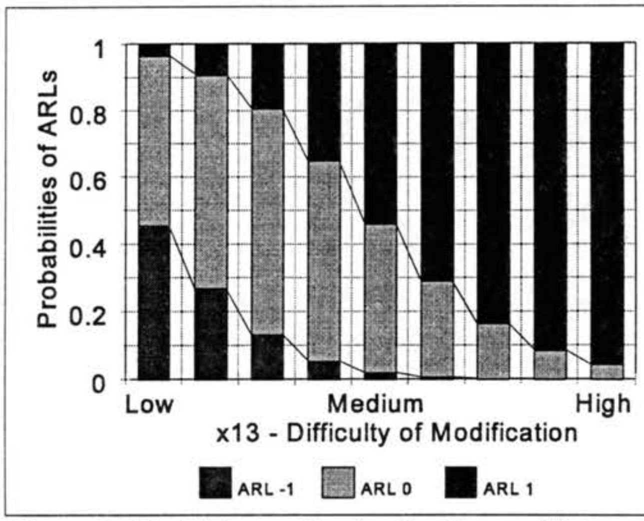

Figure 5.72. Thin saw kerf technology: effects of difficulty of modification on probabilities of ARLs (-1 vs 1).

Indivisibility has a positive, significant effect on the probability of an ARL of 1 versus an ARL of 0 ($p = .0989$). As indivisibility increases, the likelihood of an ARL of 1 increases (Figure 5.73). This supports Hypothesis 4 which suggested that higher indivisibility is associated with higher adoption resistance. Indivisibility also appears to have some differentiating ability not recognized as major in the analysis of variance.

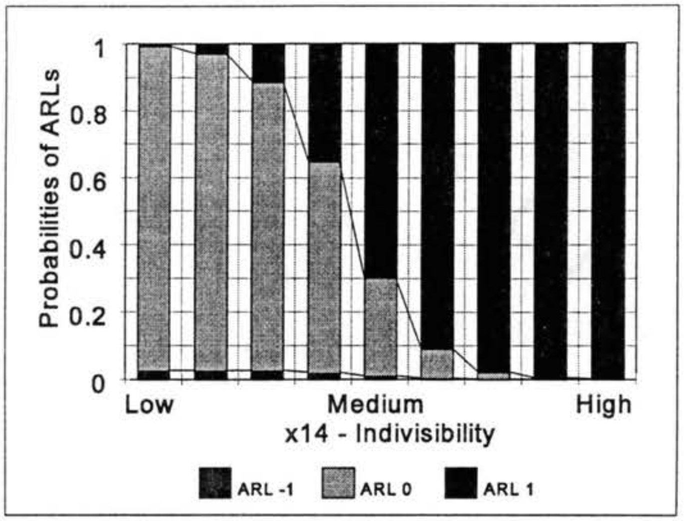

Figure 5.73. Thin saw kerf technology: effects of indivisibility on the probabilities of ARLs (1 vs 0).

5.6.1.1 Summary of thin saw kerf technology analysis, all effects

While only three variables (irreversibility, discontinuity, and past experiences) produce significant effects in the analysis of variance of thin saw kerf adoption resistance levels, several variables produce consistent significant effects spanning the continuum. Technical progressiveness.1, incompatibility, irreversibility, time to implementation, and difficulty of modification each produce a significant effect on the probability of an ARL of -1 (adoption) versus an ARL of 1 (rejection) suggesting some ability to differentiate among adoption resistance levels. All the significant effects are summarized in Table 5.23.

Table 5.23. Spans of significant effects (thin saw kerf technology model)

	Expected Direction (found the expected effect as stated in hypothesis)		Unexpected Direction (found the effect opposite from that hypothesized)	
	Spans 2 ARLs	Spans 3 ARLs	Spans 2 ARLs	Spans 3 ARLs
Technical progressiveness.1	(0 v 1)	(-1 v 1)		
Incommunicability	(0 v 1)		(-1 v 0)	
Discontinuity	(-1 v 0)		(0 v 1)	
Incompatibility	(0 v 1)	(-1 v 1)		
Irreversibility	(0 v 1)	(-1 v 1)		
Time to implementation				(-1 v 1)
Difficulty of modification		(-1 v 1)		
Indivisibility	(0 v 1)			

Irreversibility produces two significant effects that span the continuum and support the hypothesis that higher irreversibility is associated with higher adoption resistance (Hypothesis 11). It appears that firms who are likely to adopt or who have adopted thin saw kerf technology perceived this technology to be fairly easy to abandon. It also appears that firms that are likely to reject or who have rejected thin saw kerf technology perceived this technology to be fairly difficult to abandon. Therefore, to reduce adoption resistance, thin saw kerf developers may consider: keeping the price of the technology low, providing a risk-free trial period, and providing free training and installation.

Discontinuity produces conflicting significant effects with respect to support for the hypothesis that higher discontinuity is associated with higher adoption resistance. The hypothesis is supported from adoption to neutrality; from neutrality to rejection, discontinuity's effect appears to support the opposite of the hypothesis. While discontinuity appears to differentiate between levels of adoption resistance as indicated by the analysis of variance, its effect is not monotonic.

Technical progressiveness.1 produces significant effects that span the continuum and support the hypothesis that the lower the technical progressiveness of the firm, the higher the adoption resistance (Hypothesis 12). It is a characteristic of the firm and is not under the direct control of the technology developers. Since it appears that firms that make plant space available for experimentation are less likely to reject thin saw kerf technology, developers of thin saw kerf technology may consider these firms when introducing a new development. These firms would probably be more likely to adopt a new development earlier in its lifecycle and those adoptions would provide some initial capital return for the technology developer, allowing them to stay in business longer.

Factors that consistently support their respective hypotheses are technical progressiveness.1, incompatibility, irreversibility, difficulty of modification and indivisibility. Time to implementation is consistent in its support for its hypothesis. Indivisibility may affect the adoption of thin saw kerf technology only (i.e., indivisibility may not necessarily affect the rejection of thin saw kerf technology).

5.6.1.2 Goodness-of-fit for thin saw kerf technology adoption/rejection model

The overall correct classification rate for this model is 86.5%. Correct classification rates for all of the adoption resistance levels exceeded 80% (Table 5.24)! The proportional chance criterion implies that if the classifications were assigned by random, only about 36.7% of the observations would have been correctly classified. This model performed much better than that (Table 5.24), suggesting that the model fits the data very well. Also, the likelihood ratio tested insignificant (p = .9998) implying that the model fits the data well.

Table 5.24. Correct classification rates for thin saw kerf technology adoption/rejection model

ARL	Number observed	Number expected	Number correct classifications	Percentage of observations correctly predicted	Percentage of correct predictions
-1	12	11	10	83.33%	90.91%
0	19	20	17	89.47%	85.00%
1	21	21	18	85.71%	85.71%
Total	52	52	45	86.54%	86.54%

5.6.2 CNC machining

The multinomial logit model was conducted with three adopter/rejecter categories: adopt reject, and neutral. Since there are three response outcome categories, the minimum number of observations required is forty. Sixty-three observations were used in this analysis, and the observed outcomes (survey results) are given in Table 5.25.

Table 5.25. Observed levels of adoption resistance for CNC machining

Adoption resistance level (response)	Frequency of response
Adoption	28
Neutral	9
Rejection	26
Total	63

The results of the analysis of variance are provided in Table 5.26. The most significant factor in explaining variance in adoption resistance levels with respect to CNC machining is difficulty of modification (p = .1367).

Table 5.26. Analysis of variance for the CNC machining model

Source	p-value
Intercept	.3651
Technical progressiveness.1	.8130
Technical progressiveness.2	.8947
Past experiences	.3559
Firm size	.6405
Technical expertise	.1852
Incommunicability	.2541
Non-trialability	.9771
Discontinuity	.6456
Incompatibility	.2883
Irreversibility	.9710
Time to implementation	.5033
Time to realization	.8472
Difficulty of modification	.1367
Indivisibility	.2624

*Significant at $\alpha = .01$ level
**Significant at $\alpha = .05$ level
***Significant at $\alpha = .10$ level

The results of the multinomial logit analysis when benchmarked on neutral are given in Table 5.27. No factors tested significant at the $\alpha = .10$ level. Only one factor, difficulty of modification, produced significant effects at ARL 1 versus ARL -1 ($\alpha = .10$).

Table 5.27. Logit analysis of factors affecting the probability of adoption resistance level when benchmarking on neutral (CNC machining).

	Adopt (j = -1)		Reject (j = 1)	
	estimate	p-value	estimate	p-value
β_{0j} Intercept	17.3188	.2377	-9.3025	.7311
β_{1j} Technical progressiveness.1	.8809	.5700	-.0349	.9823
β_{2j} Technical progressiveness.2	2.2838	.6626	.2833	.9539
β_{3j} Past experiences	1.8065	.4518	-1.5950	.4385
β_{4j} Firm size	-11.1711	.4740	8.0593	.7637
β_{5j} Technical expertise	28.0331	.1956	-18.6271	.5522
β_{6j} Incommunicability	-.9568	.5759	-3.2664	.1071
β_{7j} Non-trialability	-.3030	.8679	-.3542	.8448
β_{8j} Discontinuity	-.8814	.3521	-.5959	.5425
β_{9j} Incompatibility	-.9211	.7762	4.1961	.2073
β_{10j} Irreversibility	.1786	.9067	-.2133	.8881
β_{11j} Time to implement	1.3682	.2458	.4578	.6742
β_{12j} Time to realization	-.6263	.5648	-.3084	.7799
β_{13j} Difficulty of modification	-2.1742	.2314	1.8115	.3081
β_{14j} Indivisibility	1.7989	.2153	-.9057	.6071

The multinomial logit model was also run with the adoption and rejection level outcomes as the benchmarks. Coefficients and p-values are given in Appendix J.

Difficulty of modification produces a significant effect at ARL -1 versus ARL 1 (-3.9857, p = .0462). The negative coefficient when benchmarking on the rejection level (ARL = 1), suggests that as difficulty of modification increases, the log odds of adoption (ARL -1) versus rejection (ARL 1) is reduced. Therefore, it appears that higher difficulty of modification is associated with higher adoption resistance and Hypothesis 10 is supported. Also, it appears that difficulty of modification is the most likely of the fourteen variables to differentiate between adoption behavior and rejection behavior.

Incommunicability produces an effect when benchmarking at ARL 0 vs ARL -1 (3.2664, $p = .1071$). Since there are so few significant effects (at $\alpha = .10$ level) and since this factor nearly triggered significance, a discussion on this factor is presented. The effect has a positive coefficient indicating that as incommunicability increases, the probability of a neutral position versus an adoption position increases. The hypothesis that higher incommunicability is associated with higher adoption resistance is somewhat supported up to the point of neutrality. Therefore, there is some support for Hypothesis 7 (at an insignificant level).

Technical expertise as measured by the number of engineers employed also produces a nearly significant effect. This effect occurred at ARL -1 vs ARL 1 (46.6602, $p = .1094$). The positive coefficient indicates that an increase in technical expertise is associated with a higher probability of a rejection position versus the probability of an adoption position when considering the adoption of CNC machinery. This does not support the hypothesis that higher technical expertise is associated with lower adoption resistance.

5.6.2.1 Summary of significant effects in CNC machining model

The only significant effect ($\alpha = .10$) is the effect of difficulty of modification on the probability of adoption versus the probability of rejection. The sign of the effect supports the hypothesis that the more difficult it is to modify a technology, the higher the adoption resistance (Hypothesis 10). Therefore, if CNC machining developers are seeking means of reducing adoption resistance, they might consider improving the ease of modification of the equipment or more effectively communicating how easy it already is to modify the equipment. However, the variable does not appear to be significant at the $\alpha = .10$ level in the analysis of variance.

5.6.2.2. Goodness-of-fit for CNC machining adoption/rejection model

A summary of the correct classification rates is given in Table 5.28. The proportional chance criterion implies that if the classifications were assigned by random, it would be expected that about 43.2% of the observations would have been correctly classified. This model's overall correct classification rate of 76.2% was much better than that (Table 5.28). However, the model was very weak in predicting neutral outcomes. This could be caused by the few observations with neutral outcomes, thereby providing insufficient data to adequately model the neutral decision. Despite this, the likelihood ratio tested insignificant (p = .9922) implying that the model fits the data well.

Table 5.28. Correct classification rates for CNC machining adoption/rejection model

ARL	Number observed	Number expected	Number correct classifications	Percentage of observations correctly predicted	Percentage of correct predictions
-1	28	30	25	89.29%	83.33%
0	9	5	2	22.22%	40.00%
1	26	28	21	80.77%	75.00%
Total	63	63	48	76.19%	76.19%

5.6.3 Water-based finishes

The multinomial logit model was conducted with three adopter/rejecter categories: adopt reject, and neutral. Sixty-six observations were used in this analysis, and the observed outcomes (survey results) are given in Table 5.29.

Table 5.29. Observed levels of adoption resistance (water-based finishes)

Adoption resistance level (response)	Frequency of response
Adoption	25
Neutral	20
Rejection	21
Total	66

Results of the analysis of variance indicate that four of the fourteen variables are significant in explaining variance in adoption resistance levels for water-based finishes. These results are summarized in Table 5.30.

Table 5.30. Analysis of variance for the water-based finishes model

Source	p-value
Intercept	.8974
Technical progressiveness.1	.6569
Technical progressiveness.2	.5278
Past experiences	.6876
Firm size	.3325
Technical expertise	.3891
Incommunicability	.0105**
Non-trialability	.3840
Discontinuity	.8705
Incompatibility	.0091*
Irreversibility	.0419**
Time to implementation	.9121
Time to realization	.0789***
Difficulty of modification	.2932
Indivisibility	.7610

*Significant at $\alpha = .01$ level
**Significant at $\alpha = .05$ level
***Significant at $\alpha = .10$ level

The results of the multinomial logit analysis when benchmarked on neutral are given in Table 5.31. Three variables tested significant at the $\alpha = .10$ level: incommunicability, incompatibility, and irreversibility. One other factor, time to realization, produced a significant effect only at ARL 1 versus ARL -1 ($p = .0246$). These are the four factors that are significant in the analysis of variance and therefore, appear to differentiate among adoption resistance levels.

Table 5.31. Logit analysis of factors affecting the probability of adoption resistance level when benchmarking on neutral (water-based finishes).

	Adopt (j = -1)		Reject (j = 1)	
	estimate	p-value	estimate	p-value
β_{0j} Intercept	5.79696	.6454	1.4005	.9485
β_{1j} Technical progressiveness.1	-.7480	.6982	-1.4169	.3611
β_{2j} Technical progressiveness.2	1.9641	.3343	1.6958	.4671
β_{3j} Past experiences	-.1391	.9419	-1.4228	.3946
β_{4j} Firm size	-25.6155	.2664	-22.4265	.2586
β_{5j} Technical expertise	30.8575	.2052	22.4420	.3866
β_{6j} Incommunicability	-6.4089	.0302**	-10.6818	.0090*
β_{7j} Non-trialability	-3.3881	.1876	-.5281	.8586
β_{8j} Discontinuity	-.4026	.6361	.0409	.9693
β_{9j} Incompatibility	-4.7177	.1763	14.3995	.0081*
β_{10j} Irreversibility	1.6877	.4416	-8.1213	.0187**
β_{11j} Time to implement	-.3880	.7282	.1788	.8638
β_{12j} Time to realization	1.3491	.2467	-2.4093	.1076
β_{13j} Difficulty of modification	-2.0156	.1551	-.0919	.9412
β_{14j} Indivisibility	-1.7063	.4686	-1.0800	.6651

* indicates significance at the $\alpha = .01$ level
** indicates significance at the $\alpha = .05$ level

The multinomial logit model was also run with the adoption and rejection level outcomes as the benchmarks. Coefficients and p-values are given in Appendix K.

Incommunicability produces two significant effects: ARL -1 versus ARL 0 (-6.4089, p = .0302) and ARL 1 versus ARL 0 (-10.6818, p = .0090). The negative coefficients associated with both effects when benchmarked on the neutral level (ARL = 0), suggest that as incommunicability increases, the log odds of neutral versus each of the other two possible outcomes is increased (Figure 5.74). Also, the negative coefficient at ARL -1 vs ARL 0 suggests that as incommunicability increases, the likelihood of an ARL of -1 decreases relative to the probability of an ARL of 0. This supports the hypothesis that higher incommunicability is associated with higher adoption resistance (Hypothesis 7). However, the other significant effect gives support to the opposite of the hypothesis. Therefore, it appears that support for Hypothesis 7 is limited to the range of adoption to neutrality. Incommunicability produces a significant effect when explaining variance in adoption resistance levels; it appears that incommunicability differentiates between adopters and rejecters.

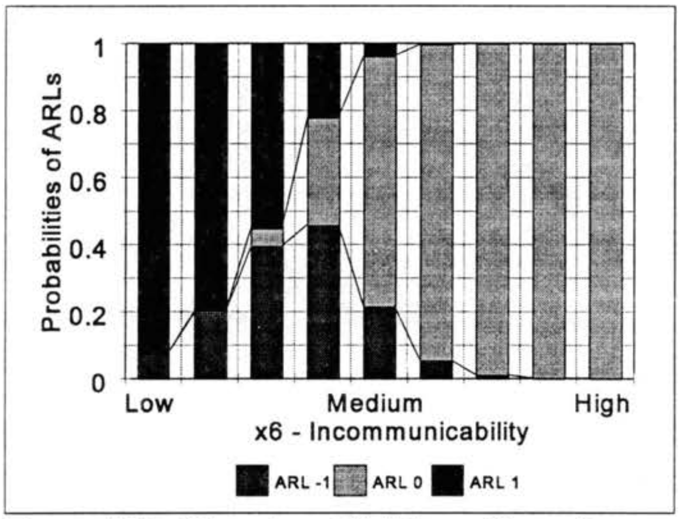

Figure 5.74. Water-based finishes: effects of incommunicability on probabilities of ARLs (-1 vs 0, 1 vs 0).

Incompatibility produces significant effects at ARL 0 versus ARL 1 ($p = .0081$) and ARL -1 versus ARL 1 ($p = .0022$). When benchmarking on the rejection position, both effects have negative coefficients. Therefore, as incompatibility increases, the likelihood of adoption or neutrality both decrease relative to the likelihood of rejection (Figure 5.75). The hypothesis that higher incompatibility is associated with higher adoption resistance (Hypothesis 1) is supported. Also, given the significant effect of incompatibility in the analysis of variance, incompatibility appears to differentiate between rejection behavior and adoption behavior.

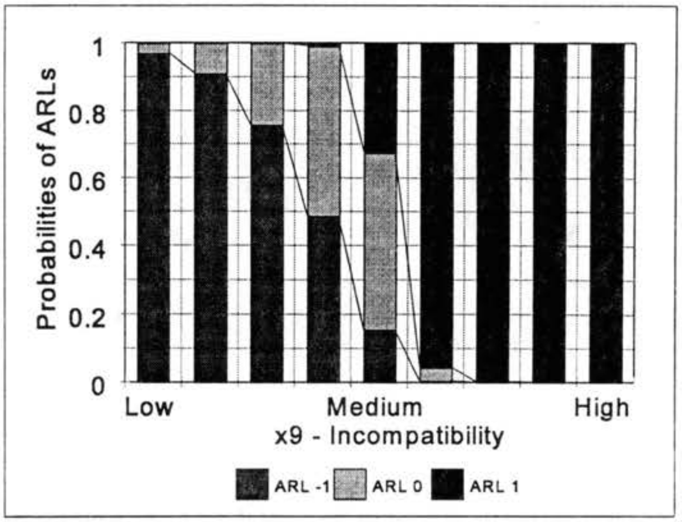

Figure 5.75. Water-based finishes: effects of incompatibility on probabilities of ARLs (-1 vs 1, 0 vs 1).

Irreversibility produces significant effects at ARL 1 vs ARL 0 ($p = .0187$), and at ARL 1 vs ARL -1 ($p = .0138$). When benchmarking on rejection (ARL 1), both effects have positive coefficients, implying that as irreversibility increases, adoption resistance decreases (confirmed in Figure 5.76). Therefore, it appears that there is support for the opposite of the hypothesis that higher irreversibility leads to higher adoption resistance (Hypothesis 11) when it comes to water-based finishes. Also, it appears that this factor differentiates between levels of adoption resistance given its significant effect in the analysis of variance.

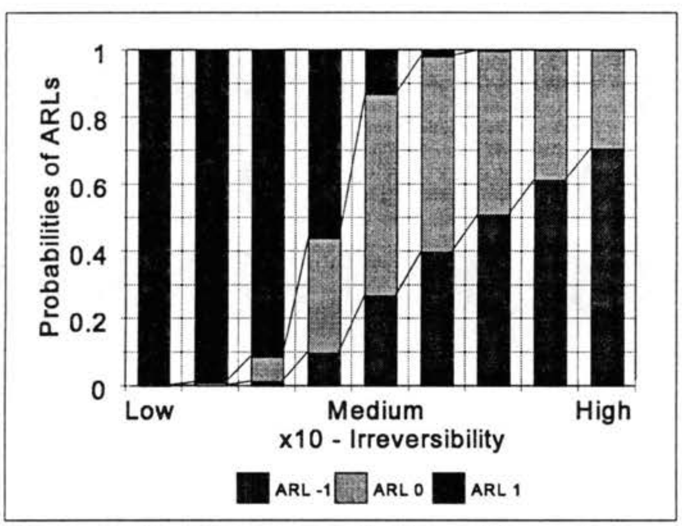

Figure 5.76. Water-based finishes: effects of irreversibility on probabilities of ARLs (-1 vs 1, 0 vs 1).

Time to realization was expected to be positively related to adoption resistance (Hypothesis 9). A significant effect is detected at ARL -1 vs ARL 1. The positive coefficient obtained when benchmarking on rejection implies that as time to realization increases, the log odds of an ARL of -1 increase versus an ARL of 1 (Figure 5.77). This is opposite from what was expected (Hypothesis 9). However, this factor does appear to differentiate between adopters and rejecters.

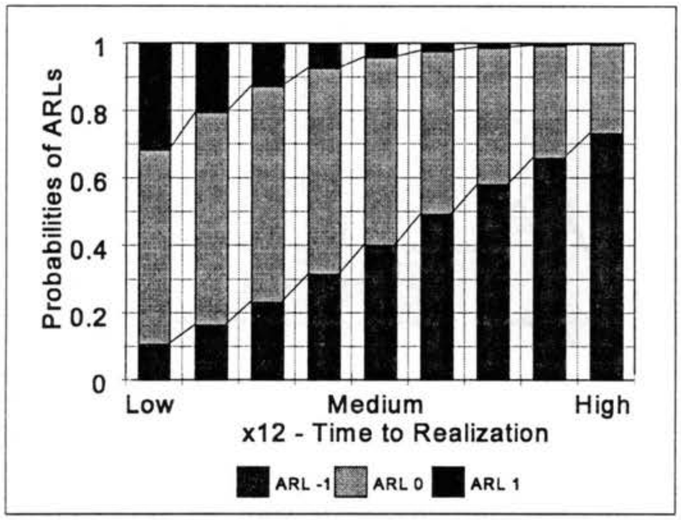

Figure 5.77. Water-based finishes: effects of time to realization on probabilities of ARLs (-1 vs 1).

5.6.3.1 Summary of significant effects of water-based finishes model

Four factors produce significant effects on the probabilities of adoption resistance levels. These are summarized in Table 5.32. These are the same four factors as those that appear to be significant in the analysis of variance. Incompatibility and irreversibility appear to have the most consistent significant effects with respect to hypothesis support. Time to realization appears to differentiate between adopters and rejecters, but does not appear to have a significant effect with respect to the neutral position. Incommunicability produces conflicting effects with respect to hypothesis support.

Table 5.32. Spans of significant effects in the water-based finishes model

	Expected Direction (found the expected effect as stated in hypothesis)		Unexpected Direction (found opposite effect from that hypothesized)	
	Spans 2 ARLs	Spans 3 ARLs	Spans 2 ARLs	Spans 3 ARLs
Incommunicability	(-1 v 0)		(1 v 0)	
Incompatibility	(0 v 1)	(-1 v 1)		
Irreversibility	(0 v 1)	(-1 v 1)		
Time to realization				(-1 v 1)

The effect of incompatibility on the water-based finishes adoption/rejection decision once again supports the hypothesis that higher incompatibility is associated with higher adoption resistance (Hypothesis 1). Incompatibility produces two consistent significant effects spanning the three level continuum. Therefore, earlier discussions on means of reducing adoption resistance through reduced incompatibility apply to developers of water-based finishes.

Irreversibility also produces two significant, consistent effects that span the three level continuum. The effects support the hypothesis that higher irreversibility is associated with higher adoption resistance (Hypothesis 11). Therefore, developers of water-based finishes might consider reducing irreversibility to reduce adoption resistance. This may mean that the finish developers would emphasize the small investment in equipment needed to change to water-based finishes so the significance of money invested would be minimized. The developers might also off to completer the change-over themselves so the manufacturer does not associate a significant amount of time with installation.

Time to realization of benefits produces a significant effect opposite from that expected. It was expected that the longer the time to realization, the higher the adoption resistance (Hypothesis 9). Information gained from telephone interviews and notes written on returned questionnaires lead to the following observation: few manufacturers surveyed perceived any benefits other than regulatory compliance to be gained through the adoption of water-based finishes. This was especially true of firms that had already adopted these finishes. It seems likely that adopters (those with low adoption resistance) may have indicated that the time to realization of benefits would be quite lengthy since they do not perceive that the realization of benefits will ever occur. Otherwise, the data suggest that one means of reducing resistance to the adoption of water-based finishes is to lengthen the time to realization of benefits.

Incommunicability produces conflicting effects with respect to the hypothesized trend of higher incommunicability being associated with higher adoption resistance. The hypothesis is supported from adoption to neutrality, but then, incommunicability's effect is opposite from that hypothesized. Therefore, it appears that while incommunicability may be a driver in the analysis of variance, it does not have uniform discriminating power.

5.6.3.2 Goodness-of-fit for water-based finishes adoption/rejection model

A summary of the correct classification rates is given in Table 5.33. The proportional chance criterion implies that if the classifications were assigned by random, it would be expected that about 32.11% of the observations would have been correctly classified. This model performed much better than that with an overall correct classification rate of 84.8% (Table 5.33). Also, the likelihood ratio tested insignificant (p = .9996) implying that the model fits the data well.

Table 5.33. Correct classification rates for water-based finishes adoption/rejection model

ARL	Number observed	Number expected	Number correct classifications	Percentage of observations correctly predicted	Percentage of correct predictions
-1	25	28	25	100.00%	89.29%
0	20	18	14	70.00%	77.78%
1	21	20	17	80.95%	85.00%
Total	66	66	56	84.85%	84.85%

5.6.4 Self-managed/cross functional work teams

The multinomial logit model was conducted with three adopter/rejecter categories: adopt reject, and neutral. Seventy-three observations were available for this analysis, and the observed outcomes (survey results) are given in Table 5.34.

Table 5.34. Observed levels of adoption resistance (self-managed/cross functional work teams)

Adoption resistance level (response)	Frequency of response
Adoption	31
Neutral	22
Rejection	20
Total	73

When benchmarking on the neutral position, the maximum likelihood estimators for twenty of the thirty estimated coefficients approach infinity. This is caused by one of two things: either there are zero frequencies in the response frequency table (Table 5.34), or there is collinearity among the estimates. Since there are no zero frequencies in the response frequency table, collinearity appears to be the cause of the infinite parameters. Pearson's correlation coefficients were calculated for the independent variables for this set of 73 observations and the results are given in Table 5.35.

There appears to be several instances of high correlation among the variables. Three pairs of variables had Pearson correlation coefficients greater than 0.50. These pairs were firm size and number of engineers (0.98); incompatibility and difficulty of modification (0.72); and non-trialability and indivisibility (0.69). With this high degree of collinearity, the maximum likelihood estimates did not converge when benchmarking on adoption. Therefore, it was concluded that the collinearity must be removed from the data through principal component analysis. However, the model would be changed at that point and the results would not be comparable to the results of analyzing the other data sets. Also, a preponderance of technology-specific evidence is already provided through the analysis of each of the hard technologies. Therefore, it was concluded that no analysis would be made for the data associated with self-managed/cross-functional work teams.

Table 5.35. Matrix of Pearson's correlation coefficients for independent variables in the self-managed/cross functional work teams model.

	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}	x_{13}	x_{14}
x_1 (tech prog.1)	.1874	.3909	-.0094	-.0050	-.0589	-.2069	-.2313	-.3668	-.1427	-.3497	-.1364	-.2959	-.0266
x_2 (tech prog.2)	1	.0675	.2558	.3385	-.1359	-.0624	-.1825	-.2521	-.3541	.2174	.3620	-.1265	-.1782
x_3 (past exper.)		1	.0704	.0749	-.2597	-.4045	-.3415	-.3798	-.0895	-.2796	-.0628	-.4519	-.1574
x_4 (firm size)			1	.9838	.1634	.2404	.0743	.0806	.1638	.1822	.2642	-.0348	.2133
x_5 (tech. expert.)				1	.1045	.2213	.0516	.0392	.1268	.1814	.2832	-.0387	.1864
x_6 (incommu.)					1	.4031	.1171	.4287	.0201	.1687	.0566	.2985	.1641
x_7 (non-trial.)						1	.4298	.4318	.1533	.3277	.2631	.3525	.6869
x_8 (discont.)							1	.4883	.2532	.3541	.1767	.3969	.4664
x_9 (incompat.)								1	.2121	.4022	.1232	.7216	.4305
x_{10} (irrev.)									1	.1622	.0588	.1060	.2539
x_{11} (TTI)										1	.4616	.3926	.1634
x_{12} (TTR)											1	.0597	.1149
x_{13} (DoM)												1	.1678
x_{14} (indiv.)													1

5.6.5 Statistical process control and PC-based production control

As mentioned before, the multinomial logit model does not typically perform well with samples that have less than twenty to thirty observations for each outcome (response) category being estimated. In this case, the number of categories being estimated is two (one category is the benchmark, and thus, the coefficients are defined to be zero), so the minimum number of observations required for meaningful analysis is forty. The observed outcomes with respect to statistical process control and PC-based production control indicate that neither one of these data sets meet this criteria (Table 5.36). Furthermore, attempts to proceed with the modeling of these two data sets resulted in failures of the maximum likelihood estimates to converge. Therefore, it was concluded that no analysis would be made for the data associated with statistical process control or pc-based production control.

Table 5.36. Observed survey results for statistical process control and PC-based production control.

	Statistical process control	PC-based production control
Adopt	9	9
Neutral	12	8
Reject	12	12
Total	33	29

5.7 Summary of significant effects for all six models

Each different analysis produced significant effects in the analysis of variance. The factors generating these effects are considered the factors that are most likely to differentiate between the levels of adoption resistance. Ten of the fourteen factors produce significant effects. A summary of the effects is given in Table 5.37.

Table 5.37. Summary of significant effects in the six models of adoption/rejection

	All techs.	Hard techs.	Soft techs.	Thin saw kerf	CNC machining	Water-based finishes
Incompat.	Significant (p = .0000)	Significant (p = .0000)	Significant (p = .0025)			Significant (p = .0091)
Difficulty of modification	Significant (p = .0036)	Significant (p = .0255)	Significant (p = .0406)		Most sig. (p = .1367)	
Irreversibility			Significant (p = .0176)	Significant (p = .0725)		Significant (p = .0419)
Time to realization			Significant (p = .0490)			Significant (p = .0789)
Incommun.		Significant (p = .0887)				Significant (p = .0105)
Technical prog.1			Significant (p = .0114)	Significant (p = .0994)		
Time to implement	Significant (p = .0499)		Significant (p = .0894)			
Discontinuity		Significant (p = .0824)		Significant (p = .0924)		
Indivisibility			Significant (p = .0535)			
Technical expertise	Significant (p = .0514)					

In addition to identifying factors that differentiate between adoption resistance levels, the analysis provides insight into whether or not the factors have a uniform or monotonic effect on adoption resistance. If the factor does have a uniform or monotonic effect across the continuum, then technology developers have a roadmap for reducing the probability of rejection and increasing the probability of adoption. A summary of the uniformity of each of the effects identified in Table 5.37 is given in Table 5.38.

Table 5.38. Uniformity of effects across the continuum

	Model					
Factor	All techs.	Hard techs.	Soft techs.	Thin saw kerf	CNC machining	Water-based finishes
Incompat.	Yes +	Yes +	Yes +			Yes +
Difficulty of modification	Yes +	Yes +	Yes +		Yes +	
Irreversibility			No	Yes +		Yes +
Time to realization			Yes +			Yes -
Incommun.		No				No
Technical prog. 1			Yes -*	Yes -		
Time to implement	No		No			
Discontinuity		No		No		
Indivisibility			Yes -			
Technical expertise	No					

(Yes + implies that a higher level of the factor was shown to produce a higher level of adoption resistance without contradiction; Yes - implies that a lower level of the factor was shown to produce a higher level of adoption resistance without contradiction)

* This factor did have one conflicting effect, but there was such a preponderance of evidence suggesting that the hypothesis was supported, that it is considered uniform in its effect.

Chapter 6. Summary and Conclusions

6.1 Summary of methods

Nine risk factors and four firm characteristics were identified as potentially having major effects on the technology adoption/rejection decision. The set of nine risk factors was comprised of incompatibility, discontinuity, non-trialability, indivisibility, incommunicability, time to implementation, time to realization, difficulty of modification, and irreversibility. The four firm characteristics were firm size, technical expertise, technical progressiveness[24] (measured two different ways), and satisfaction with past experiences. The expected impacts that each of these factors would have on the technology adoption/rejection decision were summarized in a set of hypotheses found in chapter three.

A multinomial logit model was developed using the fourteen factors. The ability of this model to explain variance in levels of technology adoption and rejection was analyzed by applying the model (with respect to six different technologies: thin saw kerf technology, CNC machining, water-based finishes, self-managed/cross functional work teams, statistical process control, and pc-based production control) to the wood products industry of the South Central United States, specifically, Arkansas, Louisiana, Mississippi, Oklahoma, and Texas. Data was collected through a mailed questionnaire and the response rate was fifteen percent. Non-response bias did not appear to exist with the possible exception of a bias towards the attitudes of larger corporations. This slight bias was not believed to affect the results and conclusions of the analysis. The model was tested using three different levels of analysis: 1) data for all six technologies, 2) data for three soft technologies and data for three hard technologies, and 3) data for each of the three hard technologies analyzed individually.

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[24]Technical progressiveness was measured with a two-item construct consisting of questions regarding a firm's attitude towards developing technical expertise and allowing for experimentation, and also with a count of trade shows attended in the last year.

6.2. Results and conclusions

The results and conclusions are drawn from the data supplied by 82 respondents in the South Central US. While data is from only a sample of a portion of the US wood products industry, the researcher believes the results can be generalized to the entire US wood products industry. Two risk factors repeatedly were found to have significant effects ($\alpha = 0.10$) on all levels of adoption resistance: incompatibility and difficulty of modification.

6.2.1 Incompatibility

Incompatibility was expected to have a positive effect on adoption resistance. In four of the six sets of data analyzed, incompatibility produced significant effects that support this hypothesis; each of these effects was significant at $\alpha = .01$ level. Results of the four analyses suggest that regardless of the scope of the analysis, incompatibility has a positive effect on technology adoption. All significant effects of incompatibility support the hypothesis that the higher the perceived incompatibility of a technology, the higher the adoption resistance. Firms that perceive high degrees of incompatibility are more likely to reject a technology than firms that perceive low degrees of incompatibility. Firms that perceive low degrees of incompatibility are more likely to adopt a technology than firms that perceive high degrees of incompatibility. This confirms Ram's (1987) proposition that compatibility may adversely affect rejection behavior and Rogers's (1983) premise that compatibility positively affects adoption behavior. This is the first time that support has been found for *both* propositions.

Incompatibility was a combination of three sub-factors: how much support upper management gave to the adoption of the technology, how much training was required to implement the technology and how well a technology fit into the current production system. Therefore, it appears that technology developers can take several steps to reduce incompatibility and thereby expect a decrease in adoption resistance. First, technology developers can provide on-site training with the purchase/acquisition of the technology. Earlier work by Oakey and O'Farrell (1992) suggested that the training issue could be one deterrent to technology adoption. This research suggests that it could also be a reason for technology rejection. Second, technology developers can improve efforts to convey the technology's advantages to the upper management of a firm and gain management's support for the technology. Management support was cited in earlier studies as a factor in the technology diffusion process (Shrivistava and Souder 1987) and the technology adoption decision (Lefebvre et al. 1991, Meredith 1987). This research found additional support for those conclusions and extended this effect to the rejection side of the continuum. Third, technology developers can increase (when possible) the options available with a technology that make it easier to fit into a particular production line (e.g., provide a translator that will work with a selection of program languages or versions for computer controlled machinery). This is consistent with earlier findings of studies concerning the adopt/don't adopt decision in which difficulty in integrating new equipment or processes with existing systems was found to be associated with non-adoption (King and Ramamurthy 1992, Skinner 1984, Oakey and O'Farrell 1992). However, the findings of this research indicate that the effect of fit with the production system extends beyond the range of adoption and nonadoption to adoption, neutrality and rejection, and thus, explains rejection behavior as well as adoption behavior.

6.2.2 Difficulty of modification

Difficulty of modification also produced consistent, continuum-spanning, significant effects in four[25] of the six data sets analyzed. Firms that perceived a technology to be difficult to modify for their production system were more likely to reject the technology than firms that perceived the technology to be less difficult to modify for their production systems. Also, firms that perceived a technology to be less difficult to modify for their production system were more likely to adopt the technology than firms that perceived the technology to be more difficult to modify for their production systems.

These results confirm Ram's (1987) previously untested proposition that increased amenability to modification reduces the probability of rejection. However, these results also indicate that increased amenability to modification increases the probability of adoption. This is a result that up to this point, the researcher had not seen in the literature. In fact, Robertson and Gatignon (1986) hypothesized that the more standardized the technology, the more rapid the adoption and diffusion of that technology would be.

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[25]One of difficulty of modification's effects was significant only at $\alpha = .14$ level. However, this was the most significant effect of any of the factors for that model.

If technology developers want to reduce the likelihood of rejection *and* increase the likelihood of adoption, then the preponderance of evidence suggests that they should look for easier means of modifying their technologies to fit into different production systems. For example, developers of thin blade saws might be able to create adjustable fittings so the blades could be fitted onto a variety of arbors.

6.2.3 Other factors affecting rejection

The characteristic, technical progressiveness appeared to have nearly full support for consistent, significant effects when analyzing the data associated with soft technologies and full support for consistent, significant effects when analyzing the data associated with thin saw kerf technology. Firms with lower levels of technical progressiveness were more likely to reject a technology than firms with higher levels of technical progressiveness and firms with higher technical expertise were more likely to adopt a technology than firms with lower levels of technical progressiveness. This extends West and Sinclair's (1992) conclusion that innovators tended to be more technologically progressive than non-innovators to the full realm of the technology adoption continuum. Again, this is a characteristic of the firm and it is not easy for technology developers to change a firm's characteristics. However, since the number of trade shows attended comprised one of the measures of technical progressiveness, technology developers might be able to reduce the probability of technology rejection and increase the probability of technology adoption by providing incentives for manufacturers to attend trade shows. The problem with this strategy is that since this is not necessarily technology-related, the result may be an increased likelihood in adopting a competitor's technology.

The risk factor indivisibility produced negative, significant, continuum-spanning effects on adoption resistance when considering soft technologies. This is not consistent with Ram's (1987) proposition that lower divisibility increases the probability of rejection. The data suggest that with respect to soft technologies, firms are more likely to adopt if they believe the technology must be implemented all at once, and they are more likely to reject if they believe the technology can be implemented in stages.

Indivisibility appeared to differentiate between adopters and rejecters of soft technologies, but it did not generate a significant effect on any of the data sets involving at least one hard technology. Therefore, it appears that indivisibility may be more pertinent to the adoption/rejection decision of soft technologies than that of hard technologies.

Time to realization produces consistent, significant effects supporting the hypothesis that longer time to realization is associated with higher adoption resistance when analyzing the soft technology data. This supports Ram's (1987) proposition that longer time to realization is associated with an increased probability of rejection. It is also consistent with Rahm and Huffman's (1984) suggestion that firms with shorter planning horizons seem to be more risk averse and less likely to adopt new technologies than firms with longer planning horizons. However, the same factor produces significant effects suggesting that shorter time to realization is associated with higher adoption resistance when analyzing the water-based finishes data. Therefore, the effect of this factor seems to be technology-dependent. For soft technology developers, decreasing the amount of time to realization of benefits or demonstrating how the benefits can be identified sooner or recognized more easily may be means of reducing adoption resistance. For developers of water-based finishes, extension of the time to realization of benefits may be one strategy for reducing the probability of rejection and increasing the probability of adoption.

Other factors that had significant effects in the analyses of variables, did not demonstrate consistent trends throughout the adoption continuum. It appears that the risk factors irreversibility, incommunicabilty, time to implementation, and discontinuity, and the characteristic technical expertise do not have unidirectional effects along the continuum. However, the explanatory power of these variables with respect to variance in adoption resistance levels, necessitates that they remain in the technology adoption/ rejection model.

Factors for which this analysis did *not* provide support for their retention in the multinomial logit model were the characteristics technical progressiveness.2, past experiences, and firm size, and the risk factor, non-trialability. Since three of the four characteristics were not supported by the model, it appears that risk factors associated with the technology itself have more impact on the technology adoption/rejection decision than the characteristics of a particular firm. Given the results of this research, non-trialability is removed from the proposed hierarchy of risk factors, resulting in the hierarchy model shown in Figure 6.1.

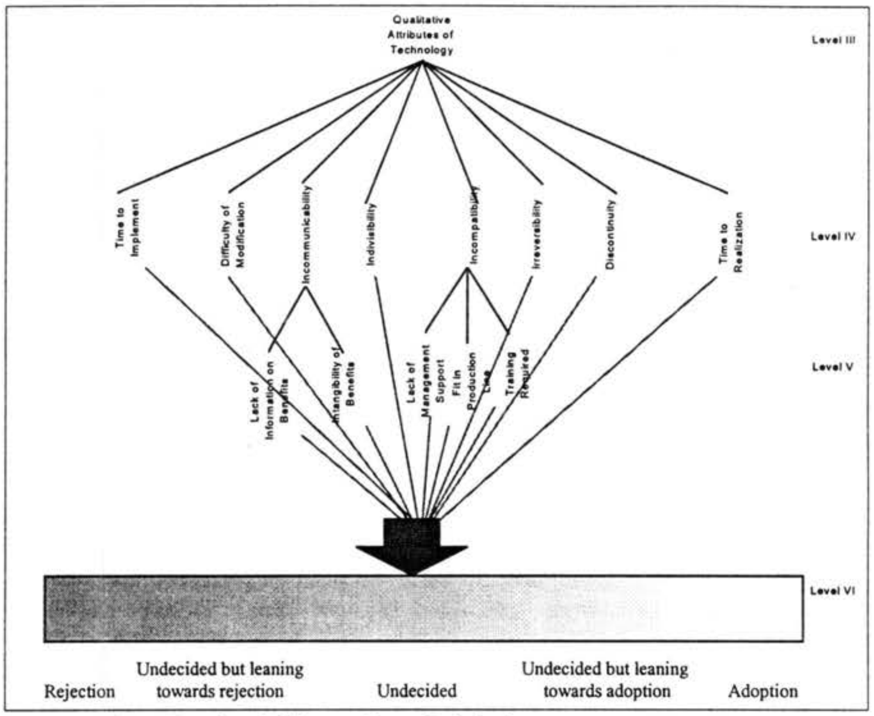

Figure 6.1. Revised hierarchy of risk factors

6.3. Implications for industry

As a result of this research, the author believes that there are several implications for firms that develop new technologies. First, risk factors related to the technology have a greater impact on adoption/rejection decisions than do firm characteristics. Therefore, marketing or technology transfer efforts should address these risk factors for an increased likelihood of success. Since incompatibility and difficulty of modification are the two most important risk factors in the technology adoption/rejection decision, firms developing new technologies should seek to transfer this technology through individuals who can understand the customer's current system, the newly developed technology, and the needs of the customer *and* who can translate this information and communicate it back to the people in the organzation who develop, design and produce the technology.

Many risk factors do not have monotonic effects on adoption resistance throughout the adoption continuum, yet differentiate among adoption resistance levels. Furthermore, whether or not certain factors increase or decrease a firm's adoption resistance is dependent upon that firm's current position on the adoption continuum. Therefore, firms developing new technologies should seek technology transfer agents (e.g., sales people, extension agents, etc.) who can assess a firm's current position along the technology adoption continuum quickly and accurately. By assessing the firm's current position and applying the results of this research, the technology transfer agent can identify which risk factors must be addressed in order to successfully transfer the technology to the potentially adopting firm.

6.4. Further research

Since this research only begins to explore the area of technology rejection, many opportunities for further research exist. The model and the methodology could be tested with other industries and other industry segments to determine if there is a set of factors that are consistent in their effects on all phases of the technology adoption continuum regardless of the industry or industry segment.

Since risk factors appear to have a greater impact on technology adoption/rejection decisions than do characteristics, research is needed to better understand the effects of the risk factors that do not exhibit monotonic effects on adoption resistance. Irreversibility, incommunicability, time to implementation, and discontinuity, and the characteristic technical expertise, should be studied further to understand and adequately describe their effects on the technology adoption/rejection decision.

The results of this research can be applied to the development of a technology evaluation decision tool. The decision tool could implement the analytical hierarchy process and would retain only those eight risk factors that proved significant in their effects. This tool, which incorporates factors that have not been previously identified as leading to rejection behavior, would be valuable to developers of technologies. The tool could be used with a small group of manufacturers to identify areas of improvement that could lead to increased adoption and decreased rejection of new technologies.

Further research is needed to develop an extension of this methodology that measures not only a firm's adoption resistance or position along the technology adoption continuum, but also the "correctness" of its decision if the position is at one of the extremes (i.e., adoption or rejection). The goal of manufacturers is not to adopt technology just to adopt technology nor to reject technology just to reject technology. The goal of manufacturers in the technology adoption/rejection decision is to adopt the right technologies for their firm. By determining a means for measuring the correctness of a decision, analyses may be conducted determining if there are certain factors that are associated with making the right decision regarding the adoption or rejection of a technology.

Since it appears that the significance of a factor's effect and the direction of that effect are dependent upon a firm's current position on the technology adoption continuum, development of conditional models would increase understanding of technology adoption and technology rejection decisions.

6.5. Significance

This research extended the work of previous technology adoption research by recognizing a continuum of outcomes of the technology adoption/rejection decision. This research explored the two sides of this continuum at once and identified factors that differentiate among all levels of the adoption research continuum; this has not been done in the past.

The results of this research expanded knowledge in several areas of industrial engineering. This research impacts the areas of technology transfer and technology management. Technology transfer models could be improved by recognizing and addressing the factors that impact technology rejection as well as those that address technology adoption. Significance of certain factors could lead to changes in the way in which technologies are developed (e.g., developers might consider easier means of modifying their products so that they can be applied in many different manufacturing environments).

Identification of factors influencing rejection behavior also contributes to the areas of multi-criteria decision making and multi-attribute evaluation of industrial projects. The risk factors identified here are rarely mentioned in the application of multi-criteria decision making tools. Integrating risk factors with more traditional economic evaluations of technology adoption costs should result in a more complete picture of the issues that should be considered in any technology acquisition model.

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Appendix A

Oklahoma State University Institutional Review Board Approval Form

for Research Involving Human Subjects

OKLAHOMA STATE UNIVERSITY
INSTITUTIONAL REVIEW BOARD
HUMAN SUBJECTS REVIEW

Date: 05-13-97 **IRB#: EG-97-004**

Proposal Title: A MODEL OF A TECHNOLOGY ADOPTION CONTINUUM INCORPORATING RISK FACTORS

Principal Investigator(s): Timothy J. Greene, Kristen G. Hoff

Reviewed and Processed as: Exempt

Approval Status Recommended by Reviewer(s): Approved

ALL APPROVALS MAY BE SUBJECT TO REVIEW BY FULL INSTITUTIONAL REVIEW BOARD AT NEXT MEETING, AS WELL AS ARE SUBJECT TO MONITORING AT ANY TIME DURING THE APPROVAL PERIOD.
APPROVAL STATUS PERIOD VALID FOR DATA COLLECTION FOR A ONE CALENDAR YEAR PERIOD AFTER WHICH A CONTINUATION OR RENEWAL REQUEST IS REQUIRED TO BE SUBMITTED FOR BOARD APPROVAL.
ANY MODIFICATIONS TO APPROVED PROJECT MUST ALSO BE SUBMITTED FOR APPROVAL.

Comments, Modifications/Conditions for Approval or Disapproval are as follows:

Signature: John H. Wycoff

Chair of Institutional Review Board

Date: May 14, 1997

cc: Kristen G. Hoff

Appendix B

Postcard announcing survey

Hello!
My name is Kris Hoff and I am a student at Oklahoma State University. As part of an ongoing research effort, I am trying to gain some insight on factors that would make it easier for wood furniture manufacturers of the South Central United States to adopt new manufacturing technologies.

In the next two weeks, you will be receiving a seven page survey. It will probably take you about 20-30 minutes to complete this survey. I realize that this is an imposition on your time, but your input could help us identify ways in which technology developers could remove some of the barriers that currently inhibit technology adoption. I would really appreciate your response to this survey.

Thank you!

Appendix C

Cover letter for first mailing

Oklahoma State University

Manufacturing Systems Engineering
322 Engineering North
Stillwater, Oklahoma 74078-0540
405-744-6055, FAX 744-6187

May 29, 1997

Mr. Stan Burch
Owner
Stans Woodshed
P O Box 176C
Paris, TX 754610176

Dear Mr. Burch:

We are conducting a survey of furniture manufacturers in the South Central United States as part of an ongoing research project at Oklahoma State University. The purpose of the project is to identify factors that influence a manufacturer's decision regarding whether or not to adopt new manufacturing technologies. By completing and returning the enclosed questionnaire, you will be providing us with valuable information that technology developers could use to make new manufacturing technologies easier to understand, acquire and implement.

Right now, we are focusing only on the wood furniture industry in the South Central United States. Therefore, your response is very important to us. When you have completed the questionnaire (it should take about 20 minutes to complete), please place it in the enclosed postage-paid, pre-addressed envelope and drop it in the mail by June 19, 1997. The information that you provide on this form will remain confidential and results will not be available on a firm-specific basis. If you would like an executive summary of the overall results of this survey, please let us know by completing the information on the last page of the questionnaire.

Thank you very much for your time and for your input!

Sincerely,

Kris Hoff

Kris Hoff
Graduate student, OSU

Appendix D

Questionnaire

I. DEMOGRAPHIC DATA

1. What is your **position** or **title**? ____________________________

2. Which of the following best describes your **company**'s situation?
____Single-plant single company ____Multi-plant, multiple companies within a corporation
____Multi-plant, single company ____Other (please specify)______________________

3. Please indicate the **state** where your plant is located:
____Arkansas ____Oklahoma
____Louisiana ____Texas
____Mississippi ____Other (please specify)______________________

4. What was the **number of people** employed by your company (not corporation, not plant) on Jan 1, 1997?
____Number of full-time **production** employees ____Number of part-time **production** employees
____Number of full-time employees **(all)** ____Number of part-time employees **(all)**

5. If your company manufactures other products besides furniture, please answer the following for **furniture production** only:
____Number of full-time **production** employees on Jan 1, 1997
____Number of full-time employees **(all)** on Jan 1, 1997
____Number of part-time **production** employees on Jan 1, 1997
____Number of part-time employees **(all)** on Jan 1, 1997

6. How many **engineers** does your firm employ?
____Number of engineers employed on Jan 1, 1997

7. What **year** did your company begin production? ____________________________

8. If your company manufactures other products besides furniture, what **year** did your company begin **furniture production**? _______________

9. What is your **primary product**?
____Wood household furniture ____Wood office furniture
____Wood store fixtures and furnishings ____Wood contract or institutional furniture
____Wood restaurant furnishings ____Wood entertainment centers
____Wood flooring ____Architectural millwork
____Wood cabinets ____Rough dimension parts
____Other (please specify)____

10. Which of the following do you **produce for sale**? (If you produce more than one of the following, please indicate the one you produce the most with a **1**, the one you produce the second most with a **2**, etc.)
____Finished goods ____Rough dimension parts
____Intermediate parts ____Other (please specify)______________
____

II. THIS NEXT SET OF QUESTIONS DEALS WITH YOUR FIRM'S TENDENCIES TO TRY NEW TECHNOLOGIES.

11. How would you respond to the following statement: Our company believes it is important to **develop expertise** on existing production technologies.
____ Strongly disagree ____ Disagree ____ Neutral ____ Agree ____ Strongly agree

12. How would you respond to the following statement: Our firm is willing to make plant space available for **experimentation** with new equipment.
____ Strongly disagree ____ Disagree ____ Neutral ____ Agree ____ Strongly agree

13. In the past year, how many **trade shows** has a representative from your firm attended?
_____ Number of trade shows

14. In general, how would you describe your firm's **past experiences** with new technology?
____ Very disappointed ____ Disappointed ____ Neutral ____ Pleased ____ Very pleased
____ Not applicable

15. Please check the items listed below which you consider **barriers** to new technology implementation.

____ Work force skills	____ Management skills
____ Financing	____ Lack of understanding the technologies
____ Facility limitations	____ Other ________________________
____ None of the above	

16. On the table at the right, please indicate which of the following best describes your firm's **awareness** of **each** technology.

	Not aware of this technology	Aware of but have not considered using	Considering, but leaning towards rejecting	Considering but leaning towards acquiring	Considering (no strong feeling towards rejecting or acquiring	Rejected the idea of using this technology after considering it	Acquired and implemented	Acquired but have already disposed of this technology
Thin saw-kerf technology								
CNC machining								
Water-based finishes								
Self-managed/cross functional work teams								
Statistical process control								
PC-based production control								

17. If you have considered using any of these technologies, please indicate the **level of interest** you have in **each** technology on the following scale (For example, if you are considering a technology and are pretty sure that you will adopt that technology, you might circle an 8 or a 9):

	Reject		→	**Still under consideration**				→	**Adopt**		
Thin saw-kerf technology:	0	1	2	3	4	5	6	7	8	9	10
CNC machining:	0	1	2	3	4	5	6	7	8	9	10
Water-based finishes:	0	1	2	3	4	5	6	7	8	9	10
Self-managed/ cross-functional work teams:	0	1	2	3	4	5	6	7	8	9	10
Statistical process control:	0	1	2	3	4	5	6	7	8	9	10
PC-based production control:	0	1	2	3	4	5	6	7	8	9	10

III. IN THIS SECTION, EACH STATEMENT OR QUESTION IS REPEATED FOR SIX DIFFERENT TECHNOLOGIES. PLEASE INDICATE YOUR RESPONSE FOR EACH TECHNOLOGY THAT YOU ARE AWARE OF.

18. THIS TECHNOLOGY **fits** easily into our production facility.

THIS TECHNOLOGY	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Thin saw-kerf technology					
CNC machining					
Water-based finishes					
Self-managed/cross functional work teams					
Statistical process control					
PC-based production control					

19. THIS TECHNOLOGY could be **easily modified** to work with our production system.

THIS TECHNOLOGY	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Thin saw-kerf technology					
CNC machining					
Water-based finishes					
Self-managed/cross functional work teams					
Statistical process control					
PC-based production control					

20. THIS TECHNOLOGY would/did require a substantial amount of **training** before implementing in our plant.

THIS TECHNOLOGY	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Thin saw-kerf technology					
CNC machining					
Water-based finishes					
Self-managed/cross functional work teams					
Statistical process control					
PC-based production control					

21. Using THIS TECHNOLOGY is/was **supported** by upper management.

THIS TECHNOLOGY	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Thin saw-kerf technology					
CNC machining					
Water-based finishes					
Self-managed/cross functional work teams					
Statistical process control					
PC-based production control					

22. There is/was sufficient opportunity to **see** the operation/application of THIS TECHNOLOGY **prior** to purchasing/applying it.

THIS TECHNOLOGY	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Thin saw-kerf technology					
CNC machining					
Water-based finishes					
Self-managed/cross functional work teams					
Statistical process control					
PC-based production control					

23. When considering this technology, how would/did you **characterize** THIS TECHNOLOGY?

THIS TECHNOLOGY	Completely new to the firm	Modification or extension of current technology
Thin saw-kerf technology		
CNC machining		
Water-based finishes		
Self-managed/cross functional work teams		
Statistical process control		
PC-based production control		

24. When considering THIS TECHNOLOGY, do/did you consider this a **major change** in the production process or a **minor change** in the production process?

THIS TECHNOLOGY	Major change	Minor change
Thin saw-kerf technology		
CNC machining		
Water-based finishes		
Self-managed/cross functional work teams		
Statistical process control		
PC-based production control		

25. How easy is it to adopt THIS TECHNOLOGY in **stages**?

THIS TECHNOLOGY	Very difficult	Difficult	Average	Easy	Very easy
Thin saw-kerf technology					
CNC machining					
Water-based finishes					
Self-managed/cross functional work teams					
Statistical process control					
PC-based production control					

26. How easy is it to **test** THIS TECHNOLOGY **using simulation** or **off-line trials** prior to adopting it?

THIS TECHNOLOGY	Very difficult	Difficult	Average	Easy	Very easy
Thin saw-kerf technology					
CNC machining					
Water-based finishes					
Self-managed/cross functional work teams					
Statistical process control					
PC-based production control					

27. THIS TECHNOLOGY can be implemented and run **in parallel with current technologies.**

THIS TECHNOLOGY	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Thin saw-kerf technology					
CNC machining					
Water-based finishes					
Self-managed/cross functional work teams					
Statistical process control					
PC-based production control					

28. Do you agree that information regarding the benefits of THIS TECHNOLOGY is **readily available**?

THIS TECHNOLOGY	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Thin saw-kerf technology					
CNC machining					
Water-based finishes					
Self-managed/cross functional work teams					
Statistical process control					
PC-based production control					

29. How difficult is it for your firm to **obtain information** regarding THIS TECHNOLOGY?

THIS TECHNOLOGY	Very difficult	Difficult	Average	Easy	Very easy
Thin saw-kerf technology					
CNC machining					
Water-based finishes					
Self-managed/cross functional work teams					
Statistical process control					
PC-based production control					

30. What are the **main benefits** you would expect if you acquired THIS TECHNOLOGY? (Mark all that apply)

THIS TECHNOLOGY	Reduced costs	Improved quality	Improved communication
Thin saw-kerf technology			
CNC machining			
Water-based finishes			
Self-managed/cross functional work teams			
Statistical process control			
PC-based production control			

31. Suppose that today, you made the decision to obtain THIS TECHNOLOGY for your plant. When do you think it would be **fully implemented**?

THIS TECHNOLOGY	Within a month	1-3 months	4-6 months	7-12 months	More than a year
Thin saw-kerf technology					
CNC machining					
Water-based finishes					
Self-managed/cross functional work teams					
Statistical process control					
PC-based production control					

32. Suppose you were to begin implementing THIS TECHNOLOGY today, when would you expect to start **seeing the expected benefits**?

THIS TECHNOLOGY	Within a month	1-3 months	4-6 months	7-12 months	More than a year
Thin saw-kerf technology					
CNC machining					
Water-based finishes					
Self-managed/cross functional work teams					
Statistical process control					
PC-based production control					

33. How would you characterize the lost time, money and effort spent on THIS TECHNOLOGY should it prove to be **ineffective** for your plant?

THIS TECHNOLOGY	Very significant	Significant	Average	Insignificant	Very insignificant
Thin saw-kerf technology					
CNC machining					
Water-based finishes					
Self-managed/cross functional work teams					
Statistical process control					
PC-based production control					

34. Do you agree that THIS TECHNOLOGY would be **difficult to abandon** if it proves ineffective?

THIS TECHNOLOGY	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Thin saw-kerf technology					
CNC machining					
Water-based finishes					
Self-managed/cross functional work teams					
Statistical process control					
PC-based production control					

35. If you have tried a technology similar to THIS TECHNOLOGY in the past, how satisfied were you with the **ease of implementation** of the similar technology?

THIS TECHNOLOGY	Very dissatisfied	Dissatisfied	Neutral	Satisfied	Very satisfied
Thin saw-kerf technology					
CNC machining					
Water-based finishes					
Self-managed/cross functional work teams					
Statistical process control					
PC-based production control					

36. If you have tried a technology similar to THIS TECHNOLOGY in the past, how satisfied were you with the **performance** of the similar technology?

THIS TECHNOLOGY	Very dissatisfied	Dissatisfied	Neutral	Satisfied	Very satisfied
Thin saw-kerf technology					
CNC machining					
Water-based finishes					
Self-managed/cross functional work teams					
Statistical process control					
PC-based production control					

37. If you have implemented any of the new technologies mentioned above, what has been your **primary source of training**?

____ Vendors
____ Vo-Tech Classes
____ Other __________________
____ College
____ Industry Associations
____ None/Not Applicable

38. Have you had difficulty in **understanding** and **complying** with any of the following? (Please check all that apply.)

	Do not understand	Some understanding	Good understanding
State and Federal Environmental Regulations			
State and Federal Workplace Safety Regulations			
Workmen's Compensation			
Equal Employment Opportunity			
Trade Mark Application and Registry			
Patent Application			

THANK YOU for your participation in this survey! An executive summary of the results of this survey will be available to all participants. If you would like to receive a copy of this summary, please indicate below.

____ **Yes,** I would like to receive an executive summary of the results of this survey.
Please send the summary to:

____

____

____

____ **No,** I would not like to receive an executive summary of the results of this survey.

Appendix E

Cover letter for second mailing

Oklahoma State University

COLLEGE OF ENGINEERING, ARCHITECTURE AND TECHNOLOGY

Research Administration
110 Engineering North
Stillwater, Oklahoma 74078-0533
405-744-5957
FAX 405-744-7545

July 22, 1997

Mr. Donald Ruebin
Owner
D & D Lockers
P O Box 69A
Gatesville, TX 765280069

Dear Mr. Ruebin:

A few weeks ago, we sent you a questionnaire regarding factors that influence a manufacturer's decision regarding whether or not to adopt new manufacturing technologies. Since we have not heard from all of the wood furniture manufacturers in the South Central United States, we thought that perhaps some of these questionnaires were lost in the mail or otherwise misplaced. So, another copy of the questionnaire is enclosed. If you did not fill out the first questionnaire or if this is the first questionnaire you have received, we would appreciate your taking a few minutes now to complete this questionnaire. We would appreciate its return as soon as possible. If you have already completed and returned the questionnaire, we thank you very much for your input and apologize for sending you this second questionnaire.

Again, your input is very valuable to us, and we thank you for sharing your time with us!

Sincerely,

Kris Hoff

Kris Hoff
Graduate student, OSU

Appendix F

Multinomial logit analysis for all technologies

Effects for all technologies

	ARL	vs.	ARL	coefficient	p-value
β_{1j}	-2	vs.	2	-.4215	.6746
	-1	vs.	2	.2946	.7616
	0	vs.	2	.2289	.7898
	1	vs.	2	-.4535	.5777
	-2	vs.	1	.0320	.9657
	-1	vs.	1	.7481	.2896
	0	vs.	1	.6824	.2104
	-2	vs.	0	-.6504	.3432
	-1	vs.	0	.0657	.9205
	-2	vs.	-1	-.7161	.3194
β_{2j}	-2	vs.	2	-.0211	.9906
	-1	vs.	2	.2719	.8798
	0	vs.	2	.1286	.9394
	1	vs.	2	-.2331	.8976
	-2	vs	1	.2120	.8693
	-1	vs	1	.5051	.6986
	0	vs	1	.3617	.7713
	-2	vs.	0	-.1497	.8670
	-1	vs.	0	.1434	.8752
	-2	vs	-1	-.2931	.7043
β_{3j}	-2	vs.	2	.4752	.6758
	-1	vs.	2	-.3375	.7609
	0	vs.	2	-.5443	.5710
	1	vs	2	-1.1426	.2140
	-2	vs.	1	1.6178	.0573
	-1	vs.	1	.8052	.3254
	0	vs	1	.5983	.3241
	-2	vs.	0	1.0195	.1921
	-1	vs.	0	-6.9337	.1974
	-2	vs	-1	2.2348	.6240

	ARL	vs.	ARL	coefficient	p-value
β_{4j}	-2	vs.	2	-6.8809	.4144
	-1	vs.	2	-9.1156	.2792
	0	vs.	2	-2.1819	.7737
	1	vs	2	-18.4332	.0326
	-2	vs.	1	11.5524	.1411
	-1	vs.	1	9.3176	.2323
	0	vs	1	16.2513	.0219
	-2	vs.	0	-4.6990	.3721
	-1	vs.	0	12.9702	.0331
	-2	vs	-1	.2253	.9593
β_{5j}	-2	vs	2	8.1998	.3228
	-1	vs	2	7.9745	.3363
	0	vs.	2	-4.9957	.5568
	1	vs.	2	11.7138	.1370
	-2	vs	1	-3.5139	.5694
	-1	vs	1	-3.7393	.5427
	0	vs.	1	-16.7094	.0070
	-2	vs.	0	13.1955	.0283
	-1	vs.	0	-.4308	.5704
	-2	vs.	-1	-.0348	.9639
β_{6j}	-2	vs	2	2.3366	.0499
	-1	vs	2	2.3715	.0377
	0	vs.	2	2.8022	.0081
	1	vs.	2	2.3679	.0209
	-2	vs	1	-.0313	.9722
	-1	vs	1	.00358	.9966
	0	vs.	1	.4343	.5348
	-2	vs.	0	.4656	.5634
	-1	vs.	0	-.5518	.4905
	-2	vs.	-1	-.1051	.8869

	ARL	vs.	ARL	coefficient	p-value
β_{7j}	-2	vs.	2	-.8307	.4567
	-1	vs.	2	-.7256	.5127
	0	vs.	2	-.1738	.8582
	1	vs.	2	-1.3683	.1422
	-2	vs.	1	.5376	.5453
	-1	vs.	1	.6427	.4628
	0	vs.	1	1.1945	.0930
	-2	vs.	0	-.6569	.4082
	-1	vs.	0	-.5518	.4905
	-2	vs.	-1	-.1051	.8869
β_{8j}	-2	vs.	2	.5715	.3141
	-1	vs.	2	.7055	.2096
	0	vs.	2	1.1217	.0313
	1	vs.	2	.8909	.0742
	-2	vs.	1	-.3194	.3795
	-1	vs.	1	-.1853	.6043
	0	vs.	1	.2309	.4271
	-2	vs.	0	.5503	.0947
	-1	vs.	0	-.4162	.2047
	-2	vs.	-1	-.1341	.6837
β_{9j}	-2	vs.	2	-9.1061	.0000
	-1	vs.	2	-6.0246	.0001
	0	vs.	2	-4.9231	.0001
	1	vs.	2	-2.2915	.0498
	-2	vs.	1	-6.8146	.0000
	-1	vs.	1	-3.7332	.0012
	0	vs.	1	-2.6316	.0017
	-2	vs.	0	-4.1829	.0002
	-1	vs.	0	-1.015	.2949
	-2	vs.	-1	-3.0814	.0056

	ARL	vs.	ARL	coefficient	p-value
β_{10j}	-2	vs.	2	-.6470	.4347
	-1	vs.	2	-.7107	.3981
	0	vs.	2	-1.4893	.0510
	1	vs.	2	-.8214	.2580
	-2	vs.	1	.1745	.7823
	-1	vs.	1	.1108	.8613
	0	vs.	1	-.6679	.2017
	-2	vs.	0	.8423	.1401
	-1	vs.	0	.7786	.1825
	-2	vs.	-1	.0637	.9095
β_{11j}	-2	vs.	2	-.9456	.1857
	-1	vs.	2	.2761	.6793
	0	vs.	2	-.6137	.2982
	1	vs.	2	-.8387	.1361
	-2	vs.	1	-.1069	.8415
	-1	vs.	1	1.1147	.0171
	0	vs.	1	.2250	.5180
	-2	vs.	0	-.3319	.5078
	-1	vs.	0	.8897	.0411
	-2	vs.	-1	-1.2216	.0192
β_{12j}	-2	vs.	2	.0227	.9728
	-1	vs.	2	-.7655	.2274
	0	vs.	2	.0389	.9455
	1	vs.	2	-.0336	.9518
	-2	vs.	1	.0563	.9093
	-1	vs.	1	-.7319	.0997
	0	vs.	1	.0725	.8309
	-2	vs.	0	-.0162	.9716
	-1	vs.	0	-.8044	.0488
	-2	vs.	-1	.7882	.0912

	ARL	vs.	ARL	coefficient	p-value
β_{13j}	-2	vs.	2	-2.2260	.0153
	-1	vs.	2	-2.1694	.0160
	0	vs.	2	-.7204	.3639
	1	vs.	2	-.0787	.9185
	-2	vs.	1	-2.1473	.0009
	-1	vs.	1	-2.0907	.0008
	0	vs.	1	-.6417	.1637
	-2	vs.	0	1.5056	.0127
	-1	vs.	0	-1.4490	.0139
	-2	vs.	-1	-.0566	.9271
β_{14j}	-2	vs.	2	.0259	.9766
	-1	vs.	2	.1884	.8338
	0	vs.	2	-.6734	.4175
	1	vs.	2	-.0577	.9428
	-2	vs.	1	.0836	.8969
	-1	vs.	1	.2461	.7105
	0	vs.	1	-.6157	.2893
	-2	vs.	0	-.6993	.2268
	-1	vs.	0	.8618	.1546
	-2	vs.	-1	-.1625	.7504

Appendix G

Multinomial logit analysis for hard technologies

Effects for hard technologies

	ARL	vs.	ARL	coefficient	p-value
β_{1j}	-2	vs.	2	-.3362	.8071
	-1	vs.	2	.0921	.9455
	0	vs.	2	-.6459	.5975
	1	vs.	2	-.9378	.4122
	-2	vs.	1	.6016	.5413
	-1	vs.	1	1.0300	.2737
	0	vs.	1	.2919	.6899
	-2	vs.	0	.3096	.7337
	-1	vs.	0	.7380	.3997
	-2	vs.	-1	-.4284	.6607
β_{2j}	-2	vs.	2	-.0573	.9821
	-1	vs.	2	1.1556	.6494
	0	vs.	2	1.3720	.5769
	1	vs.	2	.4419	.8606
	-2	vs	1	-.4992	.7653
	-1	vs	1	.7137	.6676
	0	vs	1	.9302	.5509
	-2	vs.	0	-1.4294	.1532
	-1	vs.	0	-.2165	.8277
	-2	vs	-1	-1.2129	.2190
β_{3j}	-2	vs.	2	.7682	.6180
	-1	vs.	2	-.9985	.4903
	0	vs.	2	-.4639	.7129
	1	vs	2	-1.3082	.2739
	-2	vs.	1	2.0764	.0890
	-1	vs.	1	.3098	.7782
	0	vs	1	.8443	.3058
	-2	vs.	0	1.2321	.2798
	-1	vs.	0	-.5345	.6039
	-2	vs	-1	1.7667	.1284

	ARL	vs.	ARL	coefficient	p-value
β_{4j}	-2	vs.	2	-11.3759	.2856
	-1	vs.	2	-10.5996	.3463
	0	vs.	2	-1.8507	.8399
	1	vs	2	-17.4012	.0940
	-2	vs.	1	6.0252	.5919
	-1	vs.	1	6.8015	.5607
	0	vs	1	15.5505	.1183
	-2	vs.	0	-9.5253	.1955
	-1	vs.	0	-8.7489	.2956
	-2	vs	-1	-.7763	.9259
β_{5j}	-2	vs	2	7.5622	.5380
	-1	vs	2	-1.7530	.8882
	0	vs.	2	-11.1041	.3494
	1	vs.	2	2.2332	.8336
	-2	vs	1	5.3290	.5354
	-1	vs	1	-3.9862	.6495
	0	vs.	1	-13.3373	.0912
	-2	vs.	0	18.6663	.0159
	-1	vs.	0	9.3511	.2456
	-2	vs.	-1	9.3152	.2207
β_{6j}	-2	vs	2	1.2981	.4574
	-1	vs	2	1.8723	.2627
	0	vs.	2	3.7543	.0163
	1	vs.	2	1.9035	.1830
	-2	vs	1	-.6054	.6503
	-1	vs	1	-.0312	.9799
	0	vs.	1	1.8509	.0815
	-2	vs.	0	-2.4563	.0471
	-1	vs.	0	-1.8820	.1096
	-2	vs.	-1	-.5742	.6376

	ARL	vs.	ARL	coefficient	p-value
β_{7j}	-2	vs.	2	-.0398	.9788
	-1	vs.	2	.6148	.6828
	0	vs.	2	.7070	.6042
	1	vs.	2	-.7416	.5418
	-2	vs.	1	.7018	.5538
	-1	vs.	1	1.3564	.2568
	0	vs.	1	1.4486	.1458
	-2	vs.	0	-.7468	.4673
	-1	vs.	0	-.0922	.9323
	-2	vs.	-1	-.6546	.5096
β_{8j}	-2	vs.	2	.8760	.2441
	-1	vs.	2	.9784	.1820
	0	vs.	2	1.7155	.0133
	1	vs.	2	1.0888	.0929
	-2	vs.	1	-.2128	.6755
	-1	vs.	1	-.1103	.8188
	0	vs.	1	.6267	.1232
	-2	vs.	0	-.8395	.0723
	-1	vs.	0	-.7371	.1022
	-2	vs.	-1	-.1025	.8356
β_{9j}	-2	vs.	2	-8.4903	.0000
	-1	vs.	2	-6.6823	.0009
	0	vs.	2	-6.6188	.0003
	1	vs.	2	-2.2337	.1736
	-2	vs.	1	-6.2566	.0000
	-1	vs.	1	-4.4487	.0022
	0	vs.	1	-4.3851	.0002
	-2	vs.	0	-1.8715	.1729
	-1	vs.	0	-.0635	.9616
	-2	vs.	-1	-1.8079	.1772

	ARL	vs.	ARL	coefficient	p-value
β_{10j}	-2	vs.	2	.5227	.6541
	-1	vs.	2	-.7553	.5164
	0	vs.	2	-.6212	.5554
	1	vs.	2	-.1470	.8767
	-2	vs.	1	.6697	.4737
	-1	vs.	1	-.6083	.5133
	0	vs.	1	-.4742	.5423
	-2	vs.	0	1.1439	.1778
	-1	vs.	0	-.1341	.8774
	-2	vs.	-1	1.2780	.1560
β_{11j}	-2	vs.	2	-.7099	.4479
	-1	vs.	2	.3408	.6925
	0	vs.	2	-.7530	.3354
	1	vs.	2	-.5909	.4162
	-2	vs.	1	-.1191	.8662
	-1	vs.	1	.9316	.1184
	0	vs.	1	-.1622	.7291
	-2	vs.	0	.0431	.9480
	-1	vs.	0	1.0938	.0532
	-2	vs.	-1	-1.0507	.1397
β_{12j}	-2	vs.	2	.3894	.6698
	-1	vs.	2	-.8761	.3144
	0	vs.	2	-.5310	.5118
	1	vs.	2	-.9705	.2138
	-2	vs.	1	1.3599	.0480
	-1	vs.	1	.0944	.8772
	0	vs.	1	.4395	.3868
	-2	vs.	0	.9204	.1366
	-1	vs.	0	-.3451	.5302
	-2	vs.	-1	1.2656	.0508

	ARL	vs.	ARL	coefficient	p-value
β_{13j}	-2	vs.	2	-1.8111	.1333
	-1	vs.	2	-1.2235	.2755
	0	vs.	2	.5334	.6038
	1	vs.	2	.9046	.3450
	-2	vs.	1	-2.7157	.0046
	-1	vs.	1	-2.1281	.0125
	0	vs.	1	-.3711	.5758
	-2	vs.	0	-2.3445	.0100
	-1	vs.	0	-1.7569	.0317
	-2	vs.	-1	-.5876	.5277
β_{14j}	-2	vs.	2	-2.1838	.0752
	-1	vs.	2	-1.1926	.3331
	0	vs.	2	-2.1622	.0648
	1	vs.	2	-1.6805	.1179
	-2	vs.	1	-.5034	.5739
	-1	vs.	1	.4879	.5903
	0	vs.	1	-.4817	.5453
	-2	vs.	0	-.0217	.9783
	-1	vs.	0	.9696	.2560
	-2	vs.	-1	-.9913	.2212

Appendix H

Multinomial logit analysis for soft technologies

Effects for soft technologies

	ARL	vs.	ARL	coefficient	p-value
β_{1j}	-2	vs.	2	-7.4831	.0082
	-1	vs.	2	-5.0422	.0682
	0	vs.	2	-1.4687	.5120
	1	vs.	2	-3.4267	.1290
	-2	vs.	1	-4.1051	.0306
	-1	vs.	1	-1.5807	.3884
	0	vs.	1	1.9593	.0590
	-2	vs.	0	-6.0334	.0010
	-1	vs.	0	-3.0646	.0438
	-2	vs.	-1	-2.4456	.1275
β_{2j}	-2	vs.	2	2.5895	.6539
	-1	vs.	2	1.9335	.7082
	0	vs.	2	-6.8823	.2428
	1	vs.	2	-2.5920	.5851
	-2	vs	1	6.3443	.2156
	-1	vs	1	5.6506	.2075
	0	vs	1	-4.0107	.3829
	-2	vs.	0	10.2698	.0736
	-1	vs.	0	9.5734	.0657
	-2	vs	-1	.6323	.8338
β_{3j}	-2	vs	2	.2316	.9328
	-1	vs	2	.2696	.9206
	0	vs.	2	-2.9217	.2135
	1	vs.	2	-2.7424	.2368
	-2	vs	1	3.0248	.0971
	-1	vs.	1	3.2060	.0898
	0	vs.	1	-.1836	.8780
	-2	vs.	0	3.2130	.0643
	-1	vs	0	3.3949	.0641
	-2	vs	-1	-.0296	.9859

	ARL	vs.	ARL	coefficient	p-value
β_{4j}	-2	vs.	2	-1.7294	.8279
	-1	vs.	2	-3.9984	.
	0	vs	2	4.1430	.6468
	1	vs	2	-17.8386	.1090
	-2	vs	1	14.9863	.2824
	-1	vs.	1	11.4714	.3943
	0	vs.	1	22.2530	.0898
	-2	vs	0	-7.1309	.4700
	-1	vs.	0	-10.6504	.2888
	-2	vs	-1	1.9912	.8027
β_{5j}	-2	vs	2	3.7591	.6320
	-1	vs	2	3.0716	.
	0	vs.	2	-21.8249	.0838
	1	vs.	2	4.2406	.
	-2	vs	1	.9925	.9427
	-1	vs	1	1.0790	.9361
	0	vs	1	-26.4091	.0546
	-2	vs	0	26.6998	.0464
	-1	vs.	0	26.7976	.0442
	-2	vs.	-1	.9716	.9016
β_{6j}	-2	vs	2	6.3133	.0940
	-1	vs	2	4.6834	.1531
	0	vs	2	1.0241	.7395
	1	vs.	2	3.7852	.2205
	-2	vs.	1	1.2495	.5430
	-1	vs	1	.9449	.6041
	0	vs.	1	-2.8009	.0661
	-2	vs.	0	4.0487	.0414
	-1	vs.	0	3.7450	.0333
	-2	vs	-1	.3716	.7896

	ARL	vs.	ARL	coefficient	p-value
β_{7j}	-2	vs	2	-7.1012	.0392
	-1	vs	2	-7.7825	.0237
	0	vs	2	-5.1956	.1042
	1	vs.	2	-6.4388	.0480
	-2	vs.	1	-.5887	.7670
	-1	vs	1	-1.3036	.4915
	0	vs.	1	1.2538	.3417
	-2	vs.	0	-1.8407	.3299
	-1	vs.	0	-2.5517	.1511
	-2	vs	-1	.6940	.6244
β_{8j}	-2	vs	2	-.5143	.7729
	-1	vs	2	.4850	.7866
	0	vs	2	.6865	.6802
	1	vs.	2	1.1659	.4858
	-2	vs.	1	-1.7357	.0215
	-1	vs	1	-.7365	.3345
	0	vs.	1	-.4926	.3929
	-2	vs.	0	-1.2338	.1074
	-1	vs.	0	-.2344	.7610
	-2	vs	-1	-1.0034	.1051
β_{9j}	-2	vs	2	-19.4547	.0002
	-1	vs	2	-12.9067	.0081
	0	vs	2	-4.8631	.1611
	1	vs.	2	-5.9064	.0911
	-2	vs.	1	-13.4415	.0006
	-1	vs	1	-6.8481	.0526
	0	vs.	1	1.0717	.5170
	-2	vs.	0	-14.4965	.0002
	-1	vs.	0	-7.9088	.0237
	-2	vs	-1	-6.5423	.0282

	ARL	vs.	ARL	coefficient	p-value
β_{10j}	-2	vs	2	-.7227	.7486
	-1	vs	2	.4998	.8251
	0	vs	2	-4.1209	.0366
	1	vs.	2	-1.9718	.2955
	-2	vs.	1	1.2166	.4549
	-1	vs	1	2.3315	.1471
	0	vs.	1	-2.1900	.0341
	-2	vs	0	3.4019	.0324
	-1	vs	0	4.5182	.0038
	-2	vs	-1	-1.2280	.2729
β_{11j}	-2	vs	2	-3.0064	.1557
	-1	vs	2	-1.0280	.6058
	0	vs	2	-1.7659	.3209
	1	vs	2	-2.9770	.0979
	-2	vs	1	-.1095	.9357
	-1	vs	1	1.9548	.0736
	0	vs	1	1.2212	.0933
	-2	vs.	0	-1.3338	.3262
	-1	vs.	0	.7327	.4978
	-2	vs	-1	-1.9840	.0962
β_{12j}	-2	vs	2	-2.9040	.1161
	-1	vs	2	-3.2370	.0633
	0	vs	2	.4117	.7380
	1	vs.	2	.9786	.4150
	-2	vs.	1	-3.8025	.0148
	-1	vs	1	-4.2108	.0028
	0	vs.	1	-.5564	.3976
	-2	vs.	0	-3.2296	.0274
	-1	vs.	0	-3.6378	.0053
	-2	vs	-1	.3312	.7376

	ARL	vs.	ARL	coefficient	p-value
β_{13j}	-2		2	-5.1336	.0574
	-1		2	-5.8846	.0317
	0		2	-4.5027	.0812
	1		2	-2.7742	.2855
	-2		1	-2.3537	.0480
	-1		1	-3.1077	.0201
	0		1	-1.7074	.0439
	-2		0	-.6470	.5588
	-1		0	-1.4030	.2616
	-2		-1	.7703	.5427
β_{14j}	-2		2	7.4919	.0056
	-1		2	6.5929	.0126
	0		2	3.9088	.0933
	1		2	5.0395	.0310
	-2		1	2.5420	.1446
	-1		1	1.6364	.3354
	0		1	-1.4615	.2249
	-2		0	3.9710	.0236
	-1		0	3.0652	.0746
	-2		-1	.9097	.3519

Appendix I

Multinomial logit analysis for thin saw kerf technology

Effects for thin saw kerf technology

	ARL	vs.	ARL	coefficient	p-value
β_{1j}	-1	vs.	1	10.4584	.0413
	0	vs.	1	9.7583	.0402
	-1	vs.	0	.7001	.8176
β_{2j}	-1	vs.	1	-16.1814	.5217
	0	vs.	1	5.6307	.7238
	-1	vs.	0	-21.8121	.3818
β_{3j}	-1	vs.	1	-.3996	.9292
	0	vs.	1	1.3551	.6218
	-1	vs.	0	-1.7547	.7072
β_{4j}	-1	vs.	1	27.9083	.5724
	0	vs.	1	40.3740	.2900
	-1	vs.	0	-12.4658	.7532
β_{5j}	-1	vs.	1	-8.0241	.7972
	0	vs.	1	-43.6891	.1597
	-1	vs.	0	35.6650	.3867
β_{6j}	-1	vs.	1	-6.3607	.1829
	0	vs.	1	8.2062	.0740
	-1	vs.	0	-14.5669	.0396
β_{7j}	-1	vs.	1	2.4854	.5898
	0	vs.	1	2.7648	.5148
	-1	vs.	0	-.2794	.9350
β_{8j}	-1	vs.	1	-.1166	.9669
	0	vs.	1	4.5392	.0501
	-1	vs.	0	-4.6558	.0945

	ARL	vs.	ARL	coefficient	p-value
β_{9j}	-1	vs.	1	-13.0878	.0715
	0	vs.	1	-14.4415	.0364
	-1	vs.	0	1.3537	.7061
β_{10j}	-1	vs.	1	-8.9666	.0597
	0	vs.	1	-13.7605	.0276
	-1	vs.	0	4.7938	.3273
β_{11j}	-1	vs.	1	7.9446	.0385
	0	vs.	1	4.4410	.1368
	-1	vs.	0	3.5036	.1193
β_{12j}	-1	vs.	1	2.6757	.4061
	0	vs.	1	3.8082	.1864
	-1	vs.	0	-1.1325	.6828
β_{13j}	-1	vs.	1	-5.8898	.0650
	0	vs.	1	-2.8868	.3057
	-1	vs.	0	-3.0031	.3214
β_{14j}	-1	vs.	1	-5.4966	.2087
	0	vs.	1	-5.7945	.0989
	-1	vs.	0	.2979	.9348

Appendix J

Multinomial logit analysis for CNC machining

Effects for CNC machining

	ARL	vs.	ARL	coefficient	p-value
β_{1j}	-1	vs.	1	.9158	.5799
	0	vs.	1	.0349	.9823
	-1	vs.	0	.8809	.5700
β_{2j}	-1	vs.	1	2.005	.6963
	0	vs.	1	-.2833	.9539
	-1	vs.	0	2.2838	.6626
β_{3j}	-1	vs.	1	3.4015	.1541
	0	vs.	1	1.5950	.4385
	-1	vs.	0	1.8065	.4518
β_{4j}	-1	vs.	1	-19.2304	.4498
	0	vs.	1	-8.0593	.7637
	-1	vs.	0	-11.1711	.4740
β_{5j}	-1	vs.	1	46.6602	.1094
	0	vs.	1	18.6271	.5522
	-1	vs.	0	28.0331	.1956
β_{6j}	-1	vs.	1	2.3097	.2008
	0	vs.	1	3.2664	.1071
	-1	vs.	0	-.9568	.5759
β_{7j}	-1	vs.	1	.0512	.9788
	0	vs.	1	.3542	.8448
	-1	vs.	0	-.3030	.8679
β_{8j}	-1	vs.	1	-.2855	.7495
	0	vs.	1	.5959	.5425
	-1	vs.	0	-.8814	.3521

	ARL	vs.	ARL	coefficient	p-value
β_{9j}	-1	vs.	1	-5.1172	.1387
	0	vs.	1	-4.1961	.2073
	-1	vs.	0	-.9211	.7762
β_{10j}	-1	vs.	1	.3918	.8086
	0	vs.	1	.2133	.8881
	-1	vs.	0	.1786	.9067
β_{11j}	-1	vs.	1	.9104	.4301
	0	vs.	1	-.4578	.6742
	-1	vs.	0	1.3682	.2458
β_{12j}	-1	vs.	1	-.3178	.7799
	0	vs.	1	.3084	.7799
	-1	vs.	0	-.6263	.5648
β_{13j}	-1	vs.	1	-3.9857	.0462
	0	vs.	1	-1.8115	.3081
	-1	vs.	0	-2.1742	.2314
β_{14j}	-1	vs.	1	2.0746	.1341
	0	vs.	1	.9057	.6071
	-1	vs.	0	1.7989	.2153

Appendix K

Multinomial logit analysis for water-based finishes

Effects for water-based finishes

	ARL	vs.	ARL	coefficient	p-value
β_{1j}	-1	vs.	1	.6689	.7404
	0	vs.	1	1.4169	.3611
	-1	vs.	0	-.7480	.6982
β_{2j}	-1	vs.	1	.2683	.9251
	0	vs.	1	-1.6958	.4671
	-1	vs.	0	1.9641	.3343
β_{3j}	-1	vs.	1	1.2837	.5563
	0	vs.	1	1.4228	.3946
	-1	vs.	0	-.1391	.9419
β_{4j}	-1	vs.	1	-3.1890	.9101
	0	vs.	1	22.4265	.2586
	-1	vs.	0	-25.6155	.2664
β_{5j}	-1	vs.	1	8.4156	.7804
	0	vs.	1	-22.4420	.3866
	-1	vs.	0	30.8575	.2052
β_{6j}	-1	vs.	1	4.2729	.3253
	0	vs.	1	10.6818	.0090
	-1	vs.	0	-6.4089	.0302
β_{7j}	-1	vs.	1	-2.8600	.3384
	0	vs.	1	.5281	.8586
	-1	vs.	0	-3.3881	.1876
β_{8j}	-1	vs.	1	-.4435	.6836
	0	vs.	1	-.0409	.9693
	-1	vs.	0	-.4026	.6361

	ARL	vs.	ARL	coefficient	p-value
β_{9j}	-1	vs.	1	-19.1172	.0022
	0	vs.	1	-14.3995	.0081
	-1	vs.	0	-4.7177	.1763
β_{10j}	-1	vs.	1	9.8090	.0138
	0	vs.	1	8.1213	.0187
	-1	vs.	0	1.6877	.4416
β_{11j}	-1	vs.	1	-.5668	.6757
	0	vs.	1	-.1788	.8638
	-1	vs.	0	-.3880	.7282
β_{12j}	-1	vs.	1	3.3983	.0246
	0	vs.	1	2.0493	.1076
	-1	vs.	0	1.3491	.2467
β_{13j}	-1	vs.	1	-1.9237	.1660
	0	vs.	1	.0919	.9412
	-1	vs.	0	-2.0156	.1551
β_{14j}	-1	vs.	1	-.6263	.8112
	0	vs.	1	1.0800	.6651
	-1	vs.	0	-1.7063	.4686

VITA

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