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The Assimilation of Software Process Innovations: An Organizational Learning Perspective

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The burden of organizational learning surrounding software process innovations (SPIs)—and complex organizational technologies in general—creates a "knowledge barrier" that inhibits diffusion. Attewell (1992) has suggested that many organizations will defer adoption until knowledge barriers have been sufficiently lowered; however, this leaves open the question of which organizations should be more likely to innovate, even in face of high knowledge barriers. It is proposed here that organizations will innovate in the presence of knowledge barriers when the burden of organizational learning is effectively lower, either because much of the required know-how already exists within the organization, or because such knowledge can be acquired more easily or more economically. Specifically, it is hypothesized that organizations will have a greater propensity to initiate and sustain the assimilation of SPIs when they have a greater scale of activities over which learning costs can be spread (*learning-related scale*), more extensive existing knowledge related to the focal innovation (*related knowledge*), and a greater diversity of technical knowledge and activities (*diversity*). An empirical study using data on the assimilation of object-oriented programming languages (OOPLs) by 608 information technology organizations strongly confirmed the importance of the three hypothesized factors in explaining the assimilation of OOPLs.
(*Software Process Innovation; Adoption; Diffusion; Assimilation; Organizational Learning; Object-Oriented Programming; Object Orientation; Disk-Based Survey*)

1. Introduction

This research seeks to explain differences in the propensity of firms to initiate and sustain the assimilation of complex process technologies. This work starts from Attewell's assertion that technology assimilation is best characterized as a process of organizational learning, wherein individuals and the organization as a whole acquire the knowledge and skills necessary to effectively apply the technology (Attewell 1992). According to Attewell's model, the burden of organizational learning surrounding complex technologies creates a "knowledge barrier" that inhibits diffusion. As a result, supply-side and mediating institutions must work to actively encourage diffusion by developing mechanisms that lower knowledge barriers over time. However, while this model suggests that many organizations will defer adoption until knowledge barriers have been sufficiently lowered, it says little about *which* organizations should be among the early adopters even in face of high knowledge barriers. It is proposed here that organizations will have a greater propensity to innovate with complex technologies when the burden of organizational learning is effectively lower, either because the organizations already possess much of the know-how and technical knowledge necessary to innovate, or because they can acquire such knowledge more easily or

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more economically. Specifically, it is hypothesized that information technology (IT) departments will be more likely to initiate and sustain the assimilation of software process innovations (SPIs) when they have a greater scale of activities over which learning costs can be spread (*learning-related scale*), more extensive existing knowledge in areas related to the focal innovation (*related knowledge*), and a greater diversity of technical knowledge and activities in general (*diversity*).

An empirical study is presented using data on the assimilation of object-oriented programming languages (OOPLs) by the IT departments of 608 medium to large U.S. enterprises. Following Meyer and Goes (1988), assimilation is defined as the process spanning from an organization's first awareness of an innovation to, potentially, acquisition and widespread deployment. OOPLs are a recent and prominent instance of an SPI, a broad class of technologies that includes CASE, fourth-generation languages, relational database systems, and structured methods (Fichman and Kemerer 1993a). From the perspective of IT departments, these technologies are process innovations because their deployment results in a change to the organizational process used to develop software applications. As will be argued shortly, SPIs in general, and OOPLs in particular, appear to be exemplars of technologies subject to knowledge barriers, and therefore constitute an ideal setting for testing the proposed organizational learning-based model of technology assimilation.

For researchers, this work supports and extends Attewell's reconceptualization of diffusion theory for the case of complex organizational technologies. The ultimate goal is to help both potential adopters and suppliers become more effective innovators by identifying the profile of an early and sustained SPI assimilator. For vendors, this profile provides a basis for more targeted marketing and promotion. For potential adopters, it supports a critical self-evaluation: Organizations that fit the profile are better positioned to be more aggressive adopters of new technology, and should consider adoption strategies enabled by their distinctive characteristics. However, those who do not fit the profile may wish to consider delaying adoption, or choosing a simpler technology variant.

The remainder of this article is organized as follows. Section 2 develops the theoretical basis for this work using research in organizational learning. Section 3 provides a brief overview of SPIs in general and OOPLs in particular. Section 4 describes the theoretical model and related measures. Sections 5 and 6 present the study design and empirical results, respectively. Section 7 provides a general discussion of study results, and finally, §8 summarizes major conclusions.

2. Organizational Learning and Innovation Diffusion Theory

The theoretical starting point for this research is Attewell's (1992) work linking organizational learning and innovation diffusion. Attewell provides a reconceptualization of diffusion theory for what he calls "complex organizational technologies," i.e., technologies that, when first introduced, impose a substantial burden on would-be adopters in terms of the knowledge needed to use them effectively. Such technologies typically have an abstract and demanding scientific base; tend to be "fragile" in the sense that they do not always operate as expected; are difficult to trial in a meaningful way; and are "unpackaged" in the sense that adopters cannot treat the technology as a "black box" (Tornatzky and Fleischer 1990, p. 127). SPIs have been argued to be exemplars of such technologies (Fichman and Kemerer 1993b).

While any theory of innovation incorporates communication of new information about innovations, and hence learning by potential adopters, Attewell's approach is distinguished by his explication of the *kinds* of learning involved, and the *mechanisms* by which information is acquired and propagated. Attewell draws a central distinction between the communication of "signalling" information about the existence and potential gains from using the innovation, versus know-how and technical knowledge. Classical diffusion theories implicitly focus on signalling information, and assume that a prominent factor explaining differences in innovativeness is differences in the time it takes this information to reach potential adopters. Attewell argues, however, that acquiring technical knowledge and know-how places far greater demands on potential adopters, and as a result ". . . it plays a more important role in patterning the diffusion process of complex technologies than does signalling . . . [and] should move to center stage in any theory of complex technology diffusion" (1992, p. 5).

Attewell places organizational learning at the center of his theory by focusing on institutional mechanisms that lower the burden of organizational learning surrounding adoption.[1] His theory also suggests that many organizations will defer adoption until knowledge barriers are sufficiently lowered. However, this leaves open the important question of which end-user organizations can be expected to be among the early adopters, even in face of high knowledge barriers. The answer proposed here is that they will be those organizations that are less subject to the adverse effects of knowledge barriers, for one or more of three general reasons: (1) they are better positioned than others to amortize the costs of learning, and therefore find organizational learning more affordable; (2) they have the ability to acquire any given amount of new knowledge with less effort, and therefore face a less arduous assimilation process; (3) they have less to learn about an innovation to begin with, and therefore face a less formidable learning component. These ideas are more fully developed below.

Organizations may be viewed, at any given moment, as possessing some bundle of knowledge and skills related to their current operational and managerial processes (Nelson and Winter 1982). In order to successfully assimilate a new process technology, an organization must somehow reach a state where its bundle of knowledge and skills encompasses those needed to use to the new technology effectively. Thus, an organization may be seen as having to travel some metaphorical distance to get from the current bundle to the needed bundle (Pennings and Harianto 1992). When complex technologies are first introduced, this distance is likely to be considerable for most organizations. In the case of SPIs, for example, successful assimilation requires learning on a number of fronts, including grasping the abstract principles on which the technology is based; understanding the nature of the benefits attributable to the technology; grasping specific technical features of different commercially available instances of the technology; discerning the kinds of problems to which the technology is best applied; acquiring individual skills and knowledge needed to produce a sound technical product on particular development projects; and designing appropriate organizational changes in terms of the team structure, hiring, training, and incentives.[2]

What kinds of organizations should be better able to accommodate the cost and effort of organizational learning surrounding new technologies? Attewell's description of consulting and service firms provides a clue. He notes that these organizations, by applying what they learn about new technologies in multiple client settings, are able to capture "economies of scale in learning." This suggests a closely related idea, that of *learning-related scale*, defined here as the scale of activities over which learning costs can be spread. Organizations with greater learning-related scale have a greater opportunity to capture economies of scale in learning, although this opportunity may or may not be exercised in any given instance. Learning-related scale should have a more pronounced effect on the assimilation of technologies that have high knowledge barriers because learning costs—including evaluations, trials, pilot projects, training, learning-by-doing, developing infrastructure—are likely to swamp the out-of-pocket costs of purchased products in most cases.

Organizations should be more likely to innovate when they can better afford any given level of costs associated with the journey from their current bundle

[1] These mechanisms include: mediating institutions that specialize in acquiring and propagating knowledge (such as consulting and service firms); special buyer-supplier relationships structured around learning (such as user groups); adoption by end-users as a service; and technology simplification. Although Attewell most directly articulates the specific link between learning and innovation diffusion, concepts from organizational learning are increasingly being used as a lens for examining questions related to the management of technology and innovation in general (Argote et al. 1990, Cohen and Levinthal 1990, Chew et al. 1991). For a general review of the literature, see Huber (1991).

[2] It is hard to overstate how difficult and expensive this learning process can be. Huff (1992) estimated that the five-year cost of computer-aided software engineering (CASE) tool adoption to be $35,000 per user, with the majority of this cost attributable to such learning-related activities as technology evaluation, consultants, installing a methods support group, and training. And, these estimates do not include the potentially substantial costs required to reach the point on the learning curve where performance is comparable to preexisting technologies (Kemerer 1992).

to the needed bundle of skills. They should also be more prone to innovate when they can cover the distance between their current bundle to the needed bundle with less effort and lower risk of failure. Cohen and Levinthal (1990) develop the idea that a firm's ability to appreciate an innovation, to assimilate it, and apply it to new ends—what they term its "absorptive capacity"—is largely a result of the firm's preexisting knowledge in areas related to the focal innovation. This prior *related knowledge* makes it easier for individuals to acquire and retain new knowledge because it gives individuals rich, well-organized mental schemas into which new knowledge can be placed, and allows the associative connections needed for insights related to the new knowledge. Ease of organizational learning follows from ease of individual learning, because while it has been argued that individual learning is not always sufficient for organizational learning,[3] it is certainly necessary. In addition to promoting absorptive capacity, which makes it easier and less risky to cover any given distance, related knowledge also effectively diminishes the distance a firm must travel to get from its current bundle of skills to the needed bundle, because some of the burden of knowledge acquisition is eliminated. In other words, related knowledge can be viewed as giving organizations a head start on organizational learning.

Diversity of technical knowledge and activities should also facilitate organizational learning. Cohen and Levinthal (1990) argue that diversity of knowledge contributes to absorptive capacity because it enables individuals to make novel associations and linkages involving the focal innovation; this is especially important because process technologies typically require "reinvention" (Rice and Rogers 1980) as part of the assimilation process. They also argue that when there is uncertainty about the domains from which potentially useful information may emerge, a diverse knowledge base increases the likelihood that new information will be related to what is already known. Moving to the organizational level, diversity should facilitate innovation because it increases the likelihood that an organization will have at least one domain that is sufficiently "innovation ready"—due to resources of the receiving area, or compatibility of the innovation with the receiving area—for the innovation to be introduced (Swanson 1994). In addition, in the presence of learning-by-using or other forms of increasing returns to adoption, diversity contributes to an environment where innovation can more easily be sustained, essentially because the organization can bootstrap from areas with a high fit to those with lower ones (Markus 1987, Gurbaxani 1990).

To summarize:

(1) Learning-related scale allows better amortization of learning related costs;

(2) related knowledge and diversity work together to make it easier for organizations to learn, i.e., they face less effort and risk for any given amount of knowledge to be acquired;

(3) related knowledge has an additional benefit of lowering the total quantity of required learning.

It is therefore proposed that organizations with greater learning-related scale, related knowledge, and diversity are more likely to initiate and sustain the assimilation of complex technologies.

3. Object-Oriented Programming: A Software Process Innovation

Over the past two decades, an impressive array of software process technologies have been invented. Relational databases, fourth-generation languages, CASE tools, and object technologies are just a few of the major innovations in software process technology to be commercialized since 1980. These technologies are termed *software process innovations* (SPIs) because, when acquired and deployed, they change an IT group's process for developing software applications.

While OOPLs have been developing in the academic community and R&D laboratories for over 25 years, commercially viable products have been available only since the mid to late 1980s. Most prominent among these is the C++ language, first developed in the early 1980s by Bjarne Stroustrup of AT&T Bell Laboratories, and Smalltalk, first developed in the 1970s at Xerox Parc. On a conceptual level, object-oriented principles—most notably encapsulation and inheritance—have been argued to promote such long-standing software

[3] Attewell (1992) argues, for example, that individual learning becomes organizational learning only insofar as it becomes embodied in organizational routines and practices.

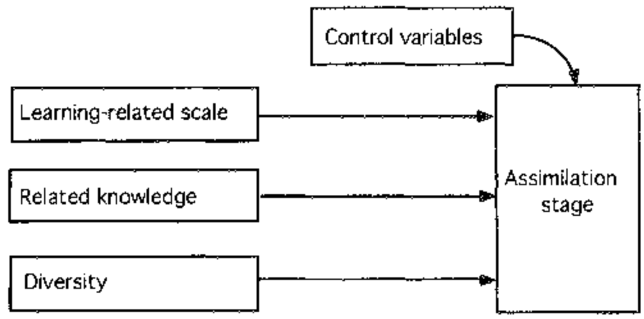
engineering goals as abstraction, modularity, reuse, maintainability, extensibility, and interoperability (Booch 1994). In a more extreme view, it has been suggested that object technology has the potential to bring about an "industrial revolution" in the way software is constructed, by transforming the current custom development process into one characterized by assembly of previously developed components (Cox 1990).

As with most SPIs, OOPLs impose a substantial burden of organizational learning on would be adopters (Fichman and Kemerer 1993b). To ensure success, adopters must have knowledge of fundamental OO principles (e.g., encapsulation, inheritance) and how to apply them; the nature of potential benefits resulting from OO (e.g., modularity, reuse, productivity) and the circumstances under which these benefits are most likely to be obtained; how to use commercial implementations of OOPL and technologies likely to be used in conjunction with OOPLs; and how to redesign team staffing, structure, procedures, and incentives in light of the radical differences between OOPLs and conventional development (Fichman and Kemerer 1992, Booch 1994). A set of four case studies of early adopters of OOPLs conducted by the authors provides a rich illustration of the knowledge burden imposed by these technologies (Fichman and Kemerer 1997).

4. Model and Measures

One of the more persistent criticisms of prior research examining the determinants of organizational innovation has been the absence of strong and consistent findings (Downs and Mohr 1976, Rogers 1983, Meyer and Goes 1988, Prescott and Conger 1995). Although a recent meta-analysis suggests that some these criticisms may have been overstated (Damanpour 1991), it is nevertheless true that studies with strong results have been comparatively rare, especially when the focal innovation has been information technology (Fichman 1992). One plausible explanation for this is that researchers, in pursuing the worthy goal of establishing a more general theory of innovation diffusion, may have been working at a theoretical level too far abstracted from particular innovations and contexts (Downs and Mohr 1976). An alternative approach—the one advocated here—is to develop theories focusing on the distinctive qualities of

Figure 1 Conceptual Model



particular kinds of technologies. Specifically, it is proposed that a greater propensity to initiate and sustain the assimilation of SPIs will be exhibited by organizations with higher learning-related scale, related knowledge, and diversity (see Figure 1). The dependent variable for this research is *assimilation stage* achieved by a given date (Meyer and Goes 1988).

4.1. Assimilation Stage

Assimilation stage may be viewed as a combined measure of earliness of initiation of assimilation activities, speed of assimilation activities, and an absence of rejection, stalling, or discontinuance (Meyer and Goes 1988). This measure provides a strong combination of both generality and richness compared with other measures (e.g., time of adoption), and is especially appropriate when studying emerging technologies such as OOPLs, because it alone among commonly used measures captures gradations of innovativeness among those yet to adopt (Fichman 1995b).

A six-stage model of SPI assimilation was employed: (1) awareness, (2) interest, (3) evaluation/trial, (4) commitment, (5) limited deployment, (6) general deployment. The model is similar to the one employed by Ettlie (1980) in his analysis of the adequacy of stage models.[4] Table 1 describes the Guttman scale used to operationalize

[4] Two changes were made. First, Ettlie's "trial" and "evaluation" stages were combined into one (evaluation/trial) because of his finding that frequently only one of these stages occurs, or they occur simultaneously. Second, Ettlie's "implementation" stage was divided into two (limited deployment and general deployment) because in many cases an SPI may be deployed on a few projects but never make the transition to a regularly used technology.

Table 1 Guttman Scale for Assimilation Stage

Stage	Criteria to Enter Stage	Survey Items Used to Classify
1. Awareness	Key decision makers are aware of the SPI	Is informant familiar with OOPL concepts or products, or aware prior OOPL-related activities at site?
2. Interest	The organization is committed to actively learning more about the SPI	Is informant aware of plans to investigate any OOPL for possible production use within next 12 months?
3. Evaluation/trial	The organization has acquired specific innovation-related products and has initiated evaluation or trial	Has site acquired any particular OOPL? Is the site evaluating or trialing any OOPL?
4. Commitment	The organization has committed to use a specific SPI product in a significant way for one or more production projects	Are any specific production projects planned, in progress, implemented or canceled that use an OOPL as the primary language?
5. Limited deployment	The organization has established a program of regular but still limited use of the SPI product	Have at least three production projects been initiated? Has at least one production project been completed?
6. General deployment	The organization has reached a state where the SPI is used on a substantial fraction of new development, including at least one large and one mission critical system	Have at least three production projects been completed? Has site implemented at least one large OOPL project requiring at least a 12 person month effort? Has one or more core or mission critical applications been completed? Has there every been a year where at least 25% of new application development projects used an OOPL?

assimilation stage for the case of OOPLs. Organizations were classified according to the highest stage achieved as of the time the survey was administered. The languages qualifying as OOPLs were identified at the beginning of the questionnaire, and all subsequent questions were asked in relation to specific languages. The review provided by Booch was used to identify the most prominent, commercially available, fully object-oriented languages (1994, Appendix). In total, six languages were selected: (1) C++, (2) Smalltalk, (3) Object Pascal, (4) Objective C, (5) Eiffel, and (6) CLOS. As of 1994, these languages accounted for over 99% of the market for OOPLs.[5]

Following Ettlie, this model proposes a linear progression through assimilation stages. Organizations may diverge from this progression by evaluating and rejecting OOPLs (rejectors), or by adopting but later discontinuing the use of OOPLs (discontinuers). Additional items were included in the survey to identify rejectors and discontinuers to allow for an analysis of any potentially distinctive properties (see Table 2).[6]

4.2. Learning-Related Scale

As discussed above, learning-related scale is the scale of activities over which learning costs can be spread. Organizations that possess greater learning-related scale should be more likely, others things being equal, to initiate and sustain innovative activities because of the opportunity for quicker and more assured payback of the substantial required investments in learning. This leads to the following hypothesis:

HYPOTHESIS 1. *Learning-Related Scale is positively related to OOPL Assimilation Stage.*

To operationalize the learning-related scale concept, two indicators were used. The first measured the number of full-time equivalent staff members developing completely new applications, while the second mea-

[5] International Data Corporation Report #10782: "1994 Worldwide Object Oriented Programming Revenues Split by Language."

[6] In point of fact, no organizations in this study had discontinued use of OOPLs; however, several had rejected, and an analysis of the properties of these organizations is provided in §6.

Table 2 Rejection and Discontinuance

Category	Criteria	Survey Items Used to Classify
Rejection	The organization has evaluated and rejected the SPI for current use.	Has the site previously evaluated and rejected OOPLs?
Discontinuance	The organization committed to using the SPI at some point in the past, but is not now using it, and does not foresee using it in the future.	Has the site ever approved an OOPL for production use? Are no projects currently pending? Has the site discontinued use?

sured the number of full-time equivalent staff members devoted to new applications together with significant enhancements to existing systems (see Appendix A). All other things being equal, more staff devoted to new development corresponds to a larger scale of new development.

While, in principle, many organizations could eventually amortize SPI-related learning costs, those with a greater volume of new applications development can amortize costs more quickly. This is particularly important because: (1) faster amortization improves return on investment; (2) managers often have little patience with investments that do not show a rapid payback; (3) intensity of effort is crucial to effective learning, yet little cumulative learning will occur if application of the new technology is infrequent (Argote et al. 1990); and (4) if a firm does not move along the internal learning curve quickly enough, then its process will be surpassed by the external learning curve (i.e., the firm could have established an efficient process faster by waiting for more mature technology vintages to become available). Furthermore, it might be argued that simply having more developers may facilitate learning more directly, by creating redundant mechanisms for communication of knowledge and innovation (Cohen and Levinthal 1990).[7]

4.3. Related Knowledge

As described above, related knowledge is the extent of abstract knowledge, know-how, and skills possessed by the organization in areas related to the focal innovation. Related knowledge facilitates assimilation by making it easier for organizations to acquire new knowledge (Cohen and Levinthal 1990), and by decreasing the total quantity of knowledge that must be acquired (Pennings and Harianto 1992). This suggests the second hypothesis:

HYPOTHESIS 2. *Related Knowledge is positively related to Assimilation Stage.*

Successful assimilation of an SPI requires that an organization possess an associated bundle of knowledge and skills, including three major components: (1) abstract principles on which the innovation is based and the skills necessary to successfully apply those principles, (2) expertise with particular specific technology products embodying the focal innovation, and (3) expertise with technologies that typically form a "cluster" around the focal innovation (Deyo et al. 1992, Scholtz et al. 1993, Fichman and Kemerer 1993b, Goldberg and Rubin 1995). For OOPLs, relevant abstract principles include encapsulation, inheritance, and message passing; particular products embodying the innovation include C++, Smalltalk, and Object Pascal (Booch 1994).

The approach to measurement employed here focuses directly on the last category of related knowledge (knowledge of technologies forming OOPLs technology cluster) and indirectly on the first category (abstract principles). Specifically, this study operationalized related knowledge as the extent of development staff experience in four areas: (1) C language programming, (2) client-server application development, (3) PC/workstation-based applications development, and (4) development of graphical user interfaces (GUIs) (see Appendix A). These four areas were identified based on discussions with OOP experts, observations made during the previously mentioned case studies of OOPL adopters, and a review of the trade press (e.g., Wallace 1993). Unlike the other variables in this study, measures for related knowledge will always be SPI-specific.

[7] We thank an anonymous reviewer for bringing this insight to our attention.

The C language is a central part of the cluster of technologies surrounding commercially available OOPLs. An organization with more extensive prior experience with C that adopts C++ (the dominant OO language) is already proficient in the sizable subset of the language that is common to C, and already possesses expertise in common supporting technologies, such as operating systems and utilities (Ambler 1993). A study conducted by IBM provides strong empirical confirmation of the link between C programming experience and proficiency in learning object-oriented programming (Liu et al. 1992). The link between OOPLs and client-server arises from the fact that the most common architecture for an OOPL-based multi-user application is client-server, with the OOPL resident on the PC or workstation-based client (Graham 1995). At the time of this study, few mature OOPL implementations existed on larger computers (mini or mainframes), and no other commonly used architecture supports both the use of an OOPL and multi-user access to data. Individuals and organizations with prior experience in client-server are spared the burden of acquiring this expertise during the course of adopting an OOPL. Another advantage of client-server expertise is that the message-passing paradigm for intermodule communication in client-server applications is also used in object-oriented applications, thus providing potential adopters with experience related to this important object-oriented principle. The relationship from OOPLs to expertise with PCs and workstations reflects the fact that when this study when done, commercially available OOPLs had been implemented almost exclusively on PC and workstation platforms (Slitz and Mintz 1993). Would-be adopters who have expertise in PC or workstation-based development already possess skills in the use of the operating systems, windowing shells, utilities, and so forth, and so are spared the burden of acquiring this knowledge in order to adopt an OOPL. The linkage between OOP and development of graphical user interfaces (GUI) stretches back to the 1970s, where Xerox PARC pioneered the GUI concept in applications built using Smalltalk. From the time OOPLs were commercialy introduced, OO applications have typically included a GUI (Taylor 1992). (This was true for all four case studies of OOPL adopters conducted by the authors.) There is also at least some overlap in terms of abstract principles and associated skills, because like OOPL applications, GUIs are event-driven and involve manipulation of objects (e.g., screen icons) (Leinfuss 1993). To summarize, the C language, client-server, PC/workstation-based development, and GUIs are all part of the OOPL technology "cluster," and additionally, overlap in terms of some specific OOP concepts and skills.

4.4. Diversity of Knowledge and Activities

As described above, diversity is the degree of heterogeneity of organizational knowledge and activities in areas related to applications development. Diversity of knowledge is a primary contributor to "absorptive capacity," which in turn facilitates organizational learning and innovation. Diversity also increases the likelihood that an organization will have at least "innovation-ready" domain around which organizational learning can begin (Swanson 1994). This suggests the third hypothesis:

HYPOTHESIS 3. *Diversity is positively related to Assimilation Stage.*

To capture diversity of technical knowledge and activities related to applications development, this research employed three indicators: (1) diversity of programming languages, (2) diversity of runtime platforms, (3) diversity of application architectures (see Appendix A). The five programming language categories (assembly language, Cobol, etc.) and seven runtime platforms (centralized mainframe, centralized mid-range, etc.) were selected to provide a parsimonious set of the most prominent languages and runtime platforms currently in use in IT departments. Six application architectures (batch MIS/transaction processing, online MIS/transaction processing, etc.) were defined based on a framework previously developed by Rumbaugh et al. (1991) to describe different computing styles. Diversity of programming languages was calculated by counting the number of different languages used on at least 5% of new applications development. Analogous methods were used to compute the measures for runtime platforms and application architectures.

4.5. Control Variables

Several variables commonly employed in prior studies of innovation diffusion were also captured to provide for greater quasi-experimental control. These include: host organization size (Rogers 1983), size of the IT function (Swanson 1994), specialization (Damanpour 1991), IT staff educational level (Brancheau and Wetherbe 1990), environmental complexity (Zmud 1984), and sector (Bretschneider and Wittmer 1993). All of these variables are expected to have positive relationships to assimilation, with one exception: Government organizations are expected to be less innovative with regard to SPIs, because of the finding by Bretschneider and Wittmer that government organizations were less innovative with respect to another information technology (i.e., microcomputers). (See Appendix A for a description of measures.)

The primary potential confound to be controlled is related to size: Since both learning-related scale and diversity can be expected to covary with more general measures of organizational size, such as total employment, organizational size is of special concern. Tornatzky and Fleischer (1990, p. 162) have argued that organizational size per se has no compelling rationale linking it to innovation, and more likely serves as a proxy for other variables, such as slack resources, education and professionalism, specialization, and scale. Included variables provide both direct (IT size, host size) and indirect (education, specialization) control for this potential confound.

Scale differs from size in that scale is defined in relation to some particular activity. While large size is usually necessary for large scale, it is not sufficient. A large machine tool manufacturer, for example, may have a large scale manufacturing operation, but a small scale marketing operation. Conversely, a large movie distribution company might have a large scale marketing operation, but a small scale manufacturing operation. For this study, learning-related scale is defined in relation to new applications development, while IT size is more broadly defined to encompass all the activities related to the IT department (development, maintenance, operations, etc.).

5. Methods

5.1. Data Collection

A mailed cross-sectional survey of IT departments in medium to large U.S.-based enterprises was used to collect the bulk of study data. The survey was disk-based, i.e., respondents were sent a computer disk containing the questionnaire items (Horton 1990, Saltzman 1993). The disk-based survey (DBS) approach is especially well suited to the target informants—IT managers—the vast majority of whom have IBM-compatible PCs on their desks at work. DBSs are outwardly similar to their paper-based counterparts, except that informants receive a computer disk instead of a hard copy questionnaire. A program automatically leads informants through the questionnaire items.[8] Although little rigorous research has been done to compare disk-based and paper-based modes, current evidence suggests that the disk-based mode does not introduce a significant bias regarding who responds, or how (Mitchell 1993, Smith 1993).

To qualify for the sampling frame, the site had to meet four criteria: (1) It had to be part of a larger enterprise with at least 500 employees; (2) it had to have reported tools for software development installed at the site; (3) it had to have an informant with an IT management-related title; and (4) it had to have Microsoft DOS or Windows-based computers on site. (The *Computerworld* database from which the sample was drawn contained the data necessary to apply these criteria, as described below.) The first two criteria increase the likelihood that custom applications development is performed at the site; the responding cases not meeting this criterion were dropped from the analysis. The third criterion helps to ensure a well-informed respondent. The last criterion was used to increase the likelihood that respondents would have readily available the means to take the survey (a DOS-based computer). This requirement only excluded an incremental 5% of the sample.

The survey instrument was developed and refined over a four-month period, following the procedures recommended by Dillman (1983). The refinement process culminated with in-person pretests at five firms. The

[8] The Ci3 authoring system, marketed by Sawtooth Software, was used to develop the DBS (Sawtooth 1992). Advantages of the DBS approach include programmable item validation; context sensitive help; sophisticated list processing capabilities; randomization; transparent branching; elimination of most kinds of informant coding errors; elimination of transcription errors and delay; and possibly, higher response rates than comparable paper-based surveys (Horton 1990, Saltzman 1993).

resulting instrument was quite lengthy and complex, with a total of 104 questions, 106 computer screens, and 35 branch points. It is felt that a questionnaire of this length and complexity simply could not have been administered using a paper-based approach. Numerous strategies were employed in an effort to boost response rates and reduce bias (Fichman 1995a).

In January 1994, a survey packet was sent to 1,500 informants that had been selected from a database (via probability sampling) maintained by International Data Corporation of 40,000 U.S. sites with computers installed.[9] A total of 679 sites returned disks, for a raw response rate of 45%. A total of 71 disks were excluded from analysis: 20 arrived after the cutoff date, 39 were from unqualified sites (i.e., no applications development) or unqualified informants (i.e., not a manager or poor self-reported knowledge of applications development), and 12 were incomplete or otherwise unusable. This left a sample size of 608 responses.

5.2. Analysis of Potential Response Bias

With a 45% raw response rate, the potential exposure of this research to a response bias is less than with many large scale surveys; nevertheless, two kinds of response bias analyses were performed. The first used the variables in the original IDC database that mapped most directly to the variables included in the theoretical model: OO adoption (a binary measure of whether any object-oriented tools were reported to be in use), IT size (the number of IS employees in the organization as a whole), host size (the number of employees in the host organization), and government (a dummy variable indicating that the sector is governmental). A logistic regression analysis was performed using OO adoption as the dependent variable and host size, IT size, and government as the independent variables. The equation was estimated first for the sample as a whole, and then just for respondents. Individual parameter estimates were quite similar, and therefore, a significant bias affecting inferences about associations seems unlikely. The second analysis was based on the responses to a 14-item telephone questionnaire developed and administered to a set of 42 randomly selected nonresponding sites. An analysis of the primary reason for nonresponse showed that neither questionnaire design itself or the disk-based method of administration was likely to have introduced much bias into who chose to respond.

5.3. Analysis of Potential Method Bias

A method bias is most likely to be a problem in studies that, like this study, use a single instrument administered to a single informant to contemporaneously measure both independent and dependent variables (Venkatraman and Ramanujarn 1987). The specific concern is that respondents will infer the "expected" relationships between variables and then shade their answers to be more consistent with the expected relationships. One test of whether a method bias might exist is to gather data on just the dependent variable, at a later time, from the same informant. The idea is that at this later time the expected relationships would not be as salient to the informant, and hence, less, if any, shading would occur. The model is then estimated using the dependent variable at Time 2, and an analysis is performed to determine whether the expected theoretical relationships still hold.

A paper-based follow-up survey was used to support an analysis of method bias. A one-page survey was constructed to measure assimilation stage.[10] A comparison of stage at Time 1 (Stage T1) and Time 2 (Stage T2) revealed a high degree of consistency between the two

[9] The goal of this database is to provide advertisers in *Computerworld* magazine—the flagship trade publication for the IT industry—with good prospects for their sales efforts. The target informants are IT professionals with buying authority for hardware, software, or telecommunications products. The selection was random, except that sites that had previously reported "Object DBMS/tools" in place (in the survey used to construct the IDC database) were two times oversampled. This was done to ensure a large enough N for planned analyses involving OOPL deployers only. To correct for this oversampling, case weighting was used in all statistical analyses. Specifically, cases were weighted so that the incidence of cases reporting "Object DBMS/tools" in place in the set of usable responses was the same as the incidence in the original sampling frame.

[10] Eight weeks after the original disks were mailed, the follow-up surveys were mailed to the 608 informants who had provided usable responses. A total of 411 surveys were returned within six weeks, for a raw response rate of 68%. Of the 411, 19 responses were not usable because of incomplete or inconsistent responses, and 9 were classified as rejectors. This left a net of 383 cases for which assimilation stage at Time 2 could be determined.

($r = 0.72$). In 89% of the cases, Stage T2 was either the same as Stage T1 or differed by only one position. Substituting Stage T2 into the analyses used to test the hypothesized model had no effect on inferences about explanatory factors. Therefore, the data provide no support for a potential methods bias.

6. Results

The vast majority of responding sites were typical IT organizations, with mainframes or midrange computers as their primary host environment (81% of respondents), and at least some MIS/transaction processing type applications (92% of respondents). The median host organization had 1,200 employees, with a maximum of 200,000. A wide range of industrial sectors were represented, including not-for-profit sectors. The largest representation was in manufacturing with 39%. The reported size of the total on-site IT staff ranged from 1 to 3,000, with a median of 16. Smaller departments were included (16% reported fewer than 5 total staff members) as well as very large (13% reported over 100 staff members). The dominant language acquired was C++. Of locations that acquired any OOPL, 94% acquired C++, 88% considered it their primary OOPL, and 67% acquired nothing but C++. For Smalltalk, these percentages were 15%, 5%, and 1%, respectively.

Table 3 confirms the particular value of assimilation stage as an innovativeness measure for recently emerged SPIs. The inclusion of the first three categories (not aware, aware, interest) captures significant variance in innovativeness that would be excluded from consideration in any of the other measures commonly used to measure innovativeness (i.e., time of adoption, dichotomous adoption, aggregated adoption, internal diffusion, infusion) (Fichman 1995b).

Table 3 OOPL Assimilation Stage

Category	Count	Percentage
0. Not aware	46	7.6
1. Aware	259	42.6
2. Interest	86	14.1
3. Evaluation/Trial	129	21.2
4. Commitment	29	4.8
5. Limited deployment	28	4.6
6. General deployment	6	1.0
Rejectors	25	4.1
Total	608	100

The primary method for data analysis was partial least squares (PLS), a second-generation multivariate technique for the estimation and assessment of structural models (Fornell and Bookstein 1982, Wold 1982, Löhmoller 1984). The PLS algorithm works iteratively to establish indicator weights and loadings while trying to fit an overall model including both measurement and structural relations (Gopal et al. 1993). After establishing indicators weights, composite scores are created as combinations of indicators times their weights. Structural paths are then fit using OLS regression based on the composite scores.

The PLS analysis was conducted in two phases. In the first phase, the measurement model was evaluated. The inward-directed indicator mode was employed in specifying the model because the constructs are viewed as formative rather than reflective. The indicators of the diversity construct, for example, are not seen as alternative reflections of diversity, but rather, as causing or comprising it (Fornell and Bookstein 1982, Johansson and Yip 1994). An inspection of the estimated indicator weights suggested that two indicators should be eliminated, one because of an unexpected negative weight (the third indicator of related knowledge), and one because of a weight of essentially zero (the third indicator of diversity) (Table 4).[11] The reduced model was reestimated, and no further problems were found.

For the five multiindicator constructs—learning-related scale, related knowledge, diversity, IT size, and education level—the average indicator variances explained were 0.96, 0.59, 0.70, 0.80, and 0.66, respectively. The average variance explained for the multiindicator constructs was 0.74, well exceeding the established criteria of 0.50 for acceptable convergent validity (Johansson and Yip 1994). In addition, there were no instances

[11] PLS imposes a fairly strict standard for inclusion of indicators in this instance. In a separate principal components analysis, all indicators loaded properly on their respective constructs. In a separate analysis of criterion validity, it was found that related knowledge and diversity were strongly associated with OOPL assimilation stage regardless of whether the original or reduced measures were used.

Table 4 Indicator Weights and Loadings

Construct	Indicator	All Indicators		Two Indicators Eliminated	
		Weight	Loading	Weight	Loading
Learning-Related Scale	L1	0.63	0.99	0.63	0.99
	L2	0.39	0.97	0.39	0.97
Related Knowledge	K1	0.69	0.81	0.62	0.87
	K2	0.31	0.60	0.27	0.65
	K3	−0.45	0.21	—	—
	K4	0.50	0.71	0.38	0.76
Diversity	D1	0.67	0.87	0.66	0.87
	D2	0.53	0.79	0.53	0.79
	D3	−0.01	0.38	—	—
IT Size	I1	0.37	0.83	0.37	0.83
	I2	0.73	0.96	0.73	0.96
Host Size	H1	1.00	1.00	1.00	1.00
Specialization	S1	1.00	1.00	1.00	1.00
Education	E1	0.64	0.83	0.64	0.83
	E2	0.59	0.80	0.59	0.80
Env. Complexity	C1	1.00	1.00	1.00	1.00
Government	G1	1.00	1.00	1.00	1.00
Assimilation Stage	A1	1.00	1.00	1.00	1.00

where a construct correlated more highly with another construct than it did with its own indicators (on average), thus assuring adequate discriminant validity (Igbaria and Greenhaus 1992). The correlations for all of the constructs expected to be associated with assimilation stage are significant (at $p \leq 0.1$) and have the expected signs (Table 5).

In the second phase, the structural model was evaluated. Table 6 provides the results for three estimated models. Model 1 is the full model, while Model 2 is a controls-only model that provides a benchmark for assessing the additional impact of the three theoretical variables. Model 3 includes only the three theoretical variables as predictors. The cells contain the path coef-

Table 5 Construct Correlations

	Assim Stage	1	2	3	4	5	6	7	8
1. Learning-Related Scale	0.38**								
2. Related Knowledge	0.34**	−0.04							
3. Diversity	0.35**	0.39**	0.11**						
4. IT Size	0.39**	0.63**	0.01	0.38*					
5. Host Size	0.15**	0.39**	−0.02	0.20**	0.41**				
6. Specialization	0.28**	0.38**	0.11**	0.34**	0.36**	0.24**			
7. Education	0.19**	0.20**	0.25**	0.17**	0.19**	0.11**	0.11**		
8. Env. Complexity	0.08*	0.02	0.14**	0.02	0.02	−0.01	0.10*	0.02	
9. Government	−0.13**	−0.03	−0.14**	−0.03	−0.08*	0.02	−0.06	−0.10*	−0.03

Table 6 Evaluation of Structural Model

	Model 1 Full Model (N = 583)	Model 2 Control Variables Only (N = 583)	Model 3 Theoretical Variables Only (N = 583)
1. Learning-Related Scale	0.21****		0.32****
	(4.5)		(8.4)
2. Related Knowledge	0.31****		0.33****
	(8.6)		(9.5)
3. Diversity	0.15***		0.19****
	(3.9)		(5.0)
4. IT Size	0.19****	0.32****	
	(4.1)	(7.3)	
5. Host Size	−0.05	−0.03	
	(−1.2)	(−0.7)	
6. Specialization	0.05	0.15***	
	(1.3)	(3.6)	
7. Education	0.00	0.11**	
	(0.1)	(2.8)	
8. Environmental Complexity	0.02	0.06	
	(0.6)	(1.6)	
9. Government	−0.05	0.08*	
	(−1.5)	(−2.1)	
Adjusted R^2	0.32	0.19	0.30
F	31.2****	23.2****	83.3****

* $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$, **** $p \leq 0.0001$.

ficients produced by PLS; these are identical to the standardized beta coefficients produced by OLS regression. OLS regression was used to compute the t statistics for the parameters, shown in parentheses.[12] An examination of the results for the full model (Model 1) reveals that the path coefficients from learning-related scale, related knowledge, and diversity to assimilation stage are all highly significant, with t statistics of 4.5, 8.6, and 3.9, respectively.[13] IT size is the only other significant predictor ($t = 4.1$) in this model. The overall model, which explains 32% of the adjusted variance, is highly significant, with an F statistic of 31.2 ($p \leq 0.0001$). A comparison of Models 1 and 2 shows that the full model

[12] PLS makes no distributional assumptions about the data, and hence, t statistics are not available. Ordinarily, the preferred approach to assessing the significance of path coefficients when using PLS is to rely on jackknife statistics (Fornell and Bookstein 1982, Wildt et al. 1982), which can be produced by the blindfolding algorithm provided by LVPLS 1.8 (Löhmoller 1984). However, LVPLS 1.8 does not support case weighting in the blindfolding algorithm. As a result, conventional t statistics produced by case-weighted OLS were viewed as more appropriate for this study. It is worth noting that the critical ratios produced by blindfolding (without case weighting) were greater than those produced by OLS (with or without case weighting). Therefore, in this instance, the OLS t statistics represent a more conservative approach to theory testing.

[13] The histogram and normal probability plot for standardized residuals both showed that residuals were close to normally distributed. A scatter plot of standardized residuals versus standardized predicted values shows no significant patterns, thus confirming the absence of heteroscedasticity. The largest condition index was CI = 2.7, well below the rule-of-thumb of CI = 10 used to identify even mild potential collinearity problems (Belsley et al. 1980). A multilevel logistic regression was also run for this model. The same predictor variables were significant, with nearly identical levels of significance. The decision to include a control variable, IT size, that covaries with a theoretical variable, learning-related scale, represents a conservative approach to testing the theoretical model, because including this control could serve to hide a genuine effect of the theoretical variable. As it happened, both variables were strongly significant when jointly included.

explains an incremental variance of 13% (32%–19%), a significant increase in variance explained (F ratio $= 39.9$, $p \leq 0.0001$). Including the control variables on top of the independent variables, by contrast, only explains an additional 2% (32%–30%) of the variance, as shown by a comparison of Models 1 and 3.

To further explore the relationship between predictor variables and assimilation stage, the mean values for the four variables with the strongest direct correlation with stage—learning-related scale, related knowledge, diversity, and IT size—were computed for each level of assimilation stage and for rejectors. Table 7 shows the ranking of the mean values from 0 (the category with the lowest mean value) to 6 (the category with the highest). The results for stage 6 must be interpreted cautiously, because of the small number of cases (six).

The data related to rejectors suggest an interesting result. The reasonable assumption that rejectors, having already evaluated an OOPL, should have predictor values at least as high other organizations still engaged in evaluation (assimilation stage 3) is not supported. In fact, the average of the predictor values is much lower for rejectors than for evaluators for all variables except related knowledge, which is consistent with the notion that organizations with comparatively low values of predictor variables are in a worse position to sustain assimilation of OOPLs.

As a final task, the plausibility of three possible threats to the validity of the base model are examined. The first threat is related to common method bias (previously discussed in §5.3). A separate analysis showed that the independent variables remain highly significant

Table 7 **Rank Order of Mean Values of Predictors by Stage**

	Learning-Related Scale	Related Knowledge	Diversity	IT Size
0. Not aware	0	0	0	0
1. Aware	1	1	1	1
2. Interest	2	2	3	2
3. Evaluation/Trial	3	3	5	4
4. Commitment	4	4	4	3
5. Limited Deployment	6	5	6	5
6. General Deployment	5	6	2	6
Rejectors	0.5	3.5	1.5	0.5

when assimilation stage measured at Time 2 is substituted into the base model, thus providing no support for the hypothesis that the results of the base model are due to the fact that the data on both predictor and outcome variables were collected at the same time with the same instrument.

The second potential validity threat is reverse causation. The specific concern is that sites may have acquired related knowledge as a result of using OOPLs. To assess this threat, a model was estimated that excluded organizations already using OOPLs (stages 4 through 6). The coefficient for related knowledge was still highly significant ($t = 4.9$; $p \leq 0.0001$), so the hypothesis that reverse causation accounts for the significant relationship in the full model is not supported by the data.

A third potential validity threat also concerns related knowledge. It might be argued that some of the indicators of this construct, particularly client-server and GUI experience, could themselves be viewed as indirect indicators of software process innovativeness. If true, this would mean the observed relationship between related knowledge and assimilation stage could result from some (unmeasured) common cause(s) of software process innovativeness. However, related knowledge is only weakly correlated with other predictor variables (Table 5). If related knowledge were, in fact, a reasonable indicator of innovativeness, then it should be strongly predicted by the same variables as assimilation stage. The fact that it is not is evidence against this alternative hypothesis.

7. Discussion

This research has strongly confirmed the expected role of organizational learning-related factors in the innovation process. Specifically, it was shown that learning-related scale, related knowledge, and diversity are all positively related to OOPL assimilation stage, and together explain 30% of the variance of this variable. The main message from these results is that organizations that are best positioned, from a structural standpoint, to accommodate the burden of organizational learning surrounding complex process technologies are more likely to initiate and sustain the assimilation of these technologies. This message holds important implications for research and practice, as described later in this section.

In terms of secondary results, it was found that while four of six control variables—IT size, specialization, education, and government—were significant predictors in the controls-only model, only one of these, IT size, significantly predicts assimilation stage in the full model. The first result supports the validity of the control variables, while the second demonstrates the potential for inappropriate inferences in the absence of the hypothesized organizational learning-related factors. Other notable results include the finding that the profile of rejectors more nearly resembles the profiles of those organizations in early stages (awareness and interest) than those in later stages (evaluation/trial, commitment, and deployment). It appears that these organizations may have taken a "quick look" at the innovation and concluded it was not for them—an outcome consistent with their comparatively adverse assimilator profile.

This study has implications for theory, methods, and practice. With regard to theory, this research supports the reconceptualization of diffusion for complex organizational technologies initiated by Attewell (1992). It maps the implications of Attewell's macrolevel model to the organizational level, identifies three organizational learning-related factors that should be of particular importance for organizational assimilation of complex organizational technologies, develops measures for these factors tailored to the SPI context, and provides statistical confirmation of their expected influence on innovation. The strong influence of related knowledge—combined with the fact that this construct does not strongly covary with "generic" innovation predictors—demonstrates the value of examining particular technologies with models that incorporate innovation-specific predictors.

The strong influence of learning-related scale and diversity—combined with the fact that these constructs *do* covary with other common innovativeness predictors—suggests that future research on SPI assimilation should seriously consider incorporating these factors to control for possible confounds. Host organization size, for example, has a significant, positive zero-order correlation with assimilation stage, but is insignificant in regressions that include these other variables. This result is consistent with Tornatzky and Fleischer's (1990) contention that the well-established empirical link between innovation and organizational size is more likely a result of other variables that covary with size—such as scale, professionalism, education, and specialization.

More generally, this research has demonstrated that it is possible to construct strongly predictive variance models, even when the focal innovation is a complex organizational technology. One of the long-standing criticisms of diffusion research has been the general weakness and instability of findings in studies predicting innovation (Downs and Mohr 1976, Rogers 1983, Meyer and Goes 1988, Fichman 1992, Prescott and Conger 1995). This research has shown that strong results can be achieved, at least when researchers confine their focus to more specific innovations and contexts, and employ theory more closely tailored to those innovations and contexts.

With regard to methods, this research confirms the value of assimilation stage as an innovativeness measure, especially when the focal technology has not yet been widely adopted. If the traditional approach of using time of adoption or dichotomous adoption for the outcome measure had been used instead, no gradations in innovativeness would have been captured for as much as 90% of the responding population, depending on the definition used for "adoption." One of the limitations of innovation research has been its typical backward-looking focus on technologies for which diffusion has already run its course. While that approach certainly has advantages, it does limit the opportunity to draw immediate, practical implications for potential users and vendors of the emerging technologies under study. In contrast, this research has identified factors affecting the assimilation of OOPLs early enough in the diffusion process for this information to be of direct practical benefit to these groups. Another contribution to research methods is confirmation of the value of the disk-based survey (DBS) mode. A survey as lengthy and complex as the one used in this research is unlikely to have been successfully administered using telephone- or paper-based survey modes. Add to this the other advantages of DBS (minimization of item nonresponse and inadvertent coding errors; elimination of transcription costs, delay, and errors) and the apparent positive effect on response rate, and one is left with a compelling case for the use of the DBS mode where feasible.

This research also has practical implications for technology vendors and mediating institutions, as well as end-users. For technology vendors and mediating institutions, this research has identified the profile of organizations more likely to initiate and sustain SPI assimilation, and in particular, OOPLs. Such organizations do more new applications development (new systems and substantial enhancements), have more extensive knowledge related to OOPLs (more experience with GUIs, the C language, etc.), and greater technical diversity in their applications development area (more programming languages, more runtime platforms). This profile provides the basis for more targeted marketing and promotion, e.g., by directing more promotion effort to appropriate specialty journals, trade shows, and technical seminars, and/or by screening prospects based on how well they fit the profile of an early assimilator. Targeted marketing is likely to be of particular value for complex organizational technologies such as SPIs, because, as Attewell has argued, broad brush "signalling" of the existence and potential benefits of such technologies is likely to be of lesser importance in promoting adoption.[14] In addition, when broadly based marketing does succeed in encouraging adoption by organizations that do not fit the assimilator profile, this could well be a pyrrhic victory, as such organizations should be less likely to sustain innovation, and may well become influential "negative" opinion leaders (Leonard-Barton 1985). Vendors and mediating institutions should rather be more focused on identifying appropriate adoption candidates, learning about the particular challenges these organizations face, and taking a more proactive role to promote successful assimilation among these sorts of organizations. Examples of such activities in the case of OOPLs abound. Many OOP language vendors have created technology consultation divisions that supply long term, on-site assistance with OOPL-based systems development. A new breed of technology consultants—referred to as "mentors"—are now available to organizations that, rather than just doing development themselves, work side-by-side with end-users with an explicit charter to teach organizations how to be successful with object technology. Vendor-sponsored user groups are another common tactic employed to facilitate successful assimilation.

The main implication of this research for end-user organizations is that they would be well advised to view SPI assimilation as a multiyear process of organizational learning, and to carefully assess the extent to which they fit the profile of an early and sustained assimilator. Do they have the opportunity to amortize learning costs afforded by a greater scale of new applications development? Do they have the greater capacity to assimilate new knowledge that results from existing knowledge in related domains, and diversity of technical knowledge in general? Do they have a head start on innovation because crucial knowledge and skills related to the innovation already exist within the organization? Successful assimilation requires sizable investments in organizational learning and process change. Considering the expense and risk involved, those that do not fit the profile should seriously consider delaying adoption, or adopting a less complex variant of the technology. If such organizations do go forward with early adoption, it should be with the understanding that risks are even higher, and so expectation management will be especially crucial.

Organizations that more closely fit the assimilator profile, by contrast, are well positioned to be comparatively vigorous in assessing emerging technologies in general, and when a decision to adopt is made, should consider undertaking assimilation strategies that exploit their inherent opportunity for more cost-effective and successful assimilation. Learning-related scale opens the option of more expensive assimilation strategies that may well be essential to success, such as hiring of experts, development of a redesigned process (and the infrastructure to support it), and allowing extended periods of "practice" on nonproduction systems. However, managers must have the wisdom and will to employ these options if they are to be of benefit in increasing the chances of successful assimilation. Related knowledge can also be extremely advantageous, but only if it is taken into account in such activities as technology selection, project selection, and the assignment of personnel to projects. Diversity increases the likelihood of an organization possessing a "safe haven"—an

[14] Bolstering this argument is the finding in this study that 92% of respondents reported some knowledge of OOPLs, and therefore had presumably already been reached by "signalling."

area where an SPI is a particularly good fit, and the conditions for learning are more ideal—and also affords the opportunity to "bootstrap" learning from areas where the technology is a higher fit, and fewer demands are made on organizational competence, to lower fit areas where successful application requires greater organizational competence. Once again, however, diversity is only an advantage for organizations that exploit it wisely.

8. Conclusions

Technological innovation is considered the primary driver of improvements in industrial productivity. Yet, if promising inventions cannot be widely deployed, then clearly the benefits resulting from their invention will be curtailed. Many have commented on the disappointingly slow rate of progress of software practice in the United States. While much of the so-called software crisis is likely attributable to undisciplined application of existing technologies and inattention to measurement and continuous improvement, incremental improvement can go only so far; at some point, more radical changes are needed to provide the base upon which further incremental improvements can be built.

Software process innovations—and complex organizational technologies more generally—impose a substantial burden on would-be adopters in terms of the know-how and technical knowledge needed to use them effectively. When knowledge barriers are high, the ability to innovate becomes at least as important as the desire or opportunity. This research has addressed the question of what kinds of organizations should be expected to innovate, even in face of high knowledge barriers. It was hypothesized that organizations with higher learning-related scale, greater related knowledge, and greater diversity of knowledge and activities would be more prone to innovate, because such organizations can better amortize learning costs, can more easily acquire the knowledge needed to innovate, and have less they have to learn to begin with. All hypotheses were strongly supported, thus validating the importance of organizational learning-related factors in explaining the assimilation of complex technologies such as software process innovations.[15]

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Appendix A: Measures

Construct	Ind	Indicator Descriptions	Mean	SD
Learning-Related Scale	L1	Log (number of application developers at site * percentage of applications-related effort attributable to new systems)	2.39	0.77
	L2	Log (number of application developers at site * percentage of applications-related effort attributable to new systems and enhancements)	2.71	0.70
Related Knowledge	K1	Percentage of development staff with experience programming in C	20.6	26.2
	K2	Percentage of development staff with experience developing client-server applications	16.9	25.9
	K3	Percentage of development staff with experience developing PC or workstation applications	38.7	33.2
	K4	Percentage of development staff with experience developing graphical user interfaces	16.5	24.6
Diversity	D1	The number of different programming languages used by ≥5% of the development staff in 1993 (assembly language, Cobol, C, other non-OO third-generation language, non-OO fourth-generation language)	2.27	1.20
	D2	The number of different runtime platforms accounting for ≥5% of new development over last 3 years (centralized mainframe, centralized midrange, client-server (CS) with mainframe host, CS with midrange host, CS with desktop host, networked workstations/PCs, standalone workstations/PCs)	2.77	1.26
	D3	The number of different application architectures accounting for ≥5% of new development over last 3 years (batch MIS/transaction processing, online MIS/transaction processing, information retrieval/reporting/query, scientific/engineering/modeling/simulation, real-time/process control, office automation/personal productivity/groupsware)	3.63	1.09

Appendix A: *Continued*

Construct	Ind	Indicator Descriptions	Mean	SD
IT Size	I1	An ordinal variable capturing level of external IT spending within respondent's span of influence (nine categories)	\$500–999k	1.35
	I2	An ordinal variable capturing number of IT employees within respondent's span of influence (nine categories)	10 to 24	1.61
Host Size	H1	Log (total number of employees in the host organization)	3.15	0.61
Specialization	S1	Sum of the number of six specialties for which the site has at least one full time staff member (technology evaluation, quality assurance, data administration, methods & tools, metrics and measurement, system testing)	1.88	1.78
Education	E1	The percentage of IT staff at the site holding bachelor's degree	65.6	31.8
	E2	The percentage of IT staff at the site holding master's degree	10.0	16.1
Environmental Complexity	C1	Mean importance of seven typical objectives for development (rapidity, cost effectiveness, schedule and budget compliance, high performance systems, high reliability systems, ease of use, ease of change) (7-point scales)	5.49	1.05
Government	G1	Binary variable coded to one for government	0.14	0.35
Assimilation Stage	A1	Stage achieved as of the time the survey was administered (ranges from 0-not aware to 6-general deployment)	2.00	1.38

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