MIS Quarterly

RESEARCH ARTICLE

A Knowledge-Based Model of Radical Innovation in Small Software Firms[1]

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In this paper, we adopt the lens of absorptive capacity (ACAP), defined by two dimensions—the knowledge base (consisting of knowledge diversity, depth, and linkages) and routines (consisting of sensing and experimentation)—to explain how a software firm's knowledge endowments influence its level of radical information technology innovation during a technological breakthrough. We distinguish three types of IT innovations—base, processes, and service innovation—that form an innovation ecology. We posit that (1) ACAP is a relational construct where the impact of the knowledge base is mediated by routines; (2) IT innovations are either externally adopted or internally generated; and (3) knowledge antecedents associated with different types of innovations differ. We hypothesize a three-step, mediated path (knowledge base → sensing → experimentation → innovation) for external innovation adoption, and a two-step path (knowledge diversity/depth → experimentation → innovation) for internal innovation creation to explain the software firm's level of radical innovation across three IT innovation types. We validate the model through a cross-sector study that examined how 121 small software firms innovated with Internet computing. We confirm the mediated nature of ACAP for external base innovations, which are driven by all three knowledge-based factors as follows: (1) knowledge depth (direct positive effect); (2) knowledge diversity (mediated three-step path), (3) knowledge linkages (mediated three step path). Process innovations are externally driven by a three-step mediated path for knowledge linkages, as well as being directly affected by knowledge diversity, but negatively and directly impeded by knowledge depth. Service innovations are not driven by any mediated influence of ACAP, but driven directly by knowledge diversity. At the same time, both service and process innovations are strongly influenced by prior IT innovations: base and/or service. Several directions for future studies of radical IT innovation are proposed.

Keywords: Absorptive capacity, knowledge base models, routines, organization knowledge base, IT innovation, innovation ecology, Internet computing, mediation

[1]Varun Grover was the accepting senior editor for this paper. Paul Pavlou served as the associate editor.

The appendices for this paper are located in the "Online Supplements" section of the *MIS Quarterly*'s website (http://www.misq.org).

Introduction

The history of information technology is one of constant change punctuated by technological breakthroughs (Lyytinen and Rose 2003a). These punctuations exemplify *radical IT innovations*—par excellence—as they erect steep barriers for any firm that aspires to innovate with these new technologies. They are especially challenging for software firms (SFs): units that envision, develop, and implement software applications for external customers. To wit, technological punctuations increase an SF's cognitive burden: its efforts to identify, assimilate, and mobilize knowledge and the related "know-how" necessary to develop new software (Attewell 1992; Fichman and Kemerer 1997; Lyytinen and Rose 2003a). Those firms, which overcome the barriers faster and with lesser difficulty, are prone to innovate more successfully, and compete more effectively in the new marketplace (Attewell 1992). In contrast, SFs that fail to garner relevant knowledge at a competitive pace continue to struggle (Lyytinen and Rose 2003b). As tectonic shifts continue to rupture the IT landscape, it remains instrumental for information systems scholars to address the question: What makes software firms more likely to innovate radically in the face of technological breakthroughs?

While answering this question, scholars face the challenge that technology-driven radical innovation in SFs is a highly complex phenomenon. From a technological perspective, it can be viewed as acquisition and application of new tools, platforms, and IT standards. From a product perspective, it can be viewed as embedding new functionality, application concepts, and design patterns into software artifacts. From a process perspective, it can be viewed as introducing changes in how software products are designed and implemented. Practically, to innovate radically, software firms need to navigate a complex and vibrant landscape of interacting innovations, which can be viewed as an "ecology" (Adomavicius et al. 2008a; Adomavicius et al. 2008b; Boland et al. 2007). Unfortunately, dominant innovation models focusing on a singular and undifferentiated IT innovation type are inadequate in understanding this phenomenon (Adomavicius et al. 2008a; Adomavicius et al. 2008b; Carlo et al. 2011). We concur with Fichman (2004, p. 314) that diffusion research focusing on a singular innovation (e.g., Prescott and Conger 1995; Lyytinen and Damsgaard 2001) "has reached the point of diminishing returns."

The next challenge is to come grips with what is meant by *radical innovation* in SFs. First, SFs produce software artifacts, which can be viewed as codified forms of heterogenous, application-domain and technological-knowledge elements. Thus *innovation* in SFs involves creation, adoption, use, and codification of novel and heterogeneous knowledge. Using a knowledge-based lens, innovation in SFs involves both external adoption and internal generation of new knowledge instrumental for creating new types of software. Second, when innovations are *radical* in SFs, they are both unique (Zaltman et al. 1973) and novel (Bijker 1992; Dahlin and Behrens 2005). Accordingly radical (IT) innovation within SFs involves the process of acquiring, assimilating, and exploiting *unique* and *novel* knowledge to create new software. Thereby, a knowledge-based perspective offers a powerful framework to explain radical IT innovation in SFs.

Recently, a growing number of studies have examined the impact of knowledge factors on innovation within SFs (Attewell 1992; Carlo et al. 2005; Fichman and Kemerer 1997; Lyytinen and Rose 2003a, 2003b). They have found that knowledge diversity (Fichman and Kemerer 1997), external linkages (Attewell 1992), and assimilative routines (Lyytinen and Rose 2003b) influence the level of innovation. None of them, however, has approached *radical* IT innovation as an ecology from a knowledge-based perspective. In constrast, studies on innovation ecologies have mostly examined interactions between innovation types or the effects of complementary assets like access to production capabilities or regulatory changes (Adomavicius et al. 2008a; Adomavicius et al. 2008b; Carlo et al. 2011; Lyytinen and Rose 2003a, 2003b). As a result, several gaps prevail for understanding innovation within SFs:

(1) What is an encompassing set of knowledge factors affecting radical IT innovation?

(2) How can these knowledge factors be organized into a knowledge-based model explaining radical IT innovation?

(3) What influence does each knowledge factor, separately and in combination, have on different types of radical IT innovation?

(4) What is the role of innovation ecologies in this processes?

To bridge these gaps, this paper formulates a *knowledge-based model of radical innovation within software firms*. The knowledge factors in the proposed model are drawn from the theory on absorptive capacity (ACAP) defined as a firm's ability to identify, acquire, integrate, and exploit knowledge for commercial ends (Cohen and Levinthal 1990; Lane et al. 2006; Zahra and George 2002). The theoretical lens of ACAP has been widely adopted in knowledge-based analyses of the firm (Lane et al. 2006; Roberts et al. 2011; Zahra and George

2002) to understand the impact of knowledge endowments on a firm's innovation and performance. However, past IS research has examined the impact of IT on ACAP, ACAP and knowledge management, and ACAP and IT assimilation (e.g., Malhotra et al. 2005; Pavlou and El Sawy 2006; Roberts et al. 2011; Srivardhana and Pawlowski 2007), but largely ignored ACAP's role as a predictor of IT innovation[2] (Roberts et al. 2011). This study, therefore, also is one of the first to unpack the dynamic nature of ACAP and view it as a multi-dimensional construct involving "interrelated capabilities" (Roberts et al. 2011, p. 641).

An SF's ACAP is defined here by two dimensions: (1) what it "knows"—its *knowledge base*; and (2) what it "does" in relation to its knowledge base—its *routines* (Cohen and Levinthal 1990; Lane et al. 2006; Roberts et al. 2011; Zahra and George 2002). In line with Roberts et al. (2011), it is posited that routines *mediate* the impact of the knowledge base on innovation outcomes during radical IT innovation. SFs are also recognized to innovate in multiple ways during technological breakthroughs involving (1) adoption and use of knowledge related to platform technologies (referred to as *base*); (2) adoption and use of knowledge associated with novel application functionality (referred to as *services*); and (3) adoption and use of knowledge in software development processes (referred to as *processes*) (Swanson 1994; Lyytinen and Rose 2003a, 2003b). These IT innovation types will have different antecedents (Grover et al. 1997), vary by their source (internal or external) (Mustonen-Ollila and Lyytinen 2003, 2004), and are differently affected by other IT innovation types within the SF's innovation ecology (Carlo et al. 2011). It is proposed (1) that different IT innovation types have different knowledge-based antecedents; (2) that knowledge factors influence different IT innovations via two types of paths (an *internal path* where innovation is spawned relying knowledge from an internal source and an *external path* where innovation is generated using an external knowledge source); and (3) different types of IT innovations are affected by other IT innovation types in varying ways. Overall, it is suggested that SFs have a greater propensity to innovate radically when they have (1) a deeper, more diverse knowledge base, with (2) intense linkages to its environment, which (3) is combined with robust and extensive sensing and experimentation routines.

Although the proposed model addresses a general research question (what sorts of knowledge endowments render an SF more likely to innovate radically during a major technological breakthrough?), the research empirically investigates radical IT innovation within small software firms (SSFs). SSFs are defined as small-sized firms that deliver software through market-based transactions to support their client organization's information processing needs. The rationale for this research design is justified by the access to a larger sampling population and the significance of small software firms in overall business innovation.

The remainder of the paper is organized as follows. First, research on radical IT innovation and absorptive capacity are reviewed. Then, a mediated, knowledge-based model for radical IT innovation with associated hypotheses is formulated. These hypotheses are then validated by a survey that examined Internet-computing innovation among 121 SSFs. Finally, the paper concludes with a discussion of implications, limitations, and potential avenues for future research.

IT Innovation in Software Firms: Definition, Nature and Types

Definition and Nature

In this study, *IT innovation* in SFs is defined as an innovation in the *application* of digital computer and communication technologies, or related organizational changes in software firms. Accordingly, the SF's *level of innovation* can be defined as the number of IT innovations it adopts. IT innovations can be further classified in the continuum of incremental to radical depending on relative differences of the innovation from preexisting alternatives (Attewell 1992; Dewar and Dutton 1986). An innovation is *radical* when innovators need to acquire extensively *unique* and *novel* technological and process-related *know-what*, *know-why*, and *know-how*. Accordingly, radical innovations can be identified by two characteristics with regard to the adopting unit (Zaltman et al. 1973). First, they are *unique* in that they differ from preexisting alternatives to the extent that those alternatives are deemed to be insufficient substitutes (Zaltman et al. 1973). Subsequently, radical innovations fundamentally drive down costs, change application scopes, their use contexts, and their delivery (Henderson and Clark 1990). Second, they are *novel* in that they rely on drastically different cognitive frames (Bijker 1992; Dahlin and Behrens 2005) so that little knowledge from previous experience can be reused in the new innovation context. This novelty is often significant enough to create prohibitively high knowledge barriers for adopting units (Attewell 1992; Fichman and Kemerer 1997). When combined, the uniqueness and novelty compel adopting units to displace their highly invested knowledge competencies and to engage in risky, ambiguous, and resource-intensive learning.

[2]Based on a systematic review of literature in 2004, 2009, and 2010 with ABI Inform and Google Scholar.

SF Innovation Ecology: Three Types of IT Innovation and Their Sources

As suggested by the notion of an ecology, IT innovations do not come in one form (Swanson 1994). An SF's ecology thus includes innovations that vary by heterogeneity, scarcity, and the amount and scope of required knowledge (Damanpour 1991; Grover et al. 1997; Subramanian and Nilakanta 1996; Swanson 1994; Wilson et al. 1999). Therefore, a proper identification of the *type* of IT innovation is critical in understanding knowledge factors that affect each IT innovation, and also its interactions with other IT innovations. In identifying the type of IT innovation, we draw upon the tripartite model of IT innovation proposed by Lyytinen and Rose (2003a, 2003b). We select this taxonomy for three reasons. First, it provides an exhaustive way to identify IT innovations carried out by an SF. Second, the classification not only recognizes the substantial differences among IT innovations, but also their mutual interdependencies necessary to discern an SF's innovation ecology (Carlo et al. 2011; Swanson 1994). Third, prior research shows that these three innovation types have different antecedents (Adomavicius et al. 2008a; Adomavicius et al. 2008b; Grover et al. 1997), suggesting that unique combinations of knowledge endowments will influence each IT innovation type (Subramanian 1996; Wilson et al. 1999). These IT innovations within the ecology can also vary by source (Mustonen-Ollila and Lyytinen 2003, 2004), that is, they can be created internally within a firm or adopted externally from its environment (Cohen and Levinthal 1990).

Lyytinen and Rose's tripartite model identifies three IT innovation types: base, process, and service.[3] *Base innovations* involve changes in computing capabilities and related architectures available to SFs to design and implement software. This includes identifying, assimilating, and deploying knowledge about computing architectures, principles and their systemic connections as reflected in discoveries in operating systems, telecommunication software, middleware, programming languages, and so on. Due to economies of scale and scope, and the scarcity of high-level technical talent, most SFs adopt these innovations and assimilate related knowledge from their external environment[4] (Cohen and Levinthal 1990). SFs learn to *use* this knowledge while delivering their software (Messerschmitt and Szyperski 2003). The incentives for SFs to engage in base innovation include improved efficiency, new services/products, or the need to imitate competitors (Messerschmitt and Szyperski 2003). A base innovation is radical when it involves configuration of available computing resources in unique and novel ways, which significantly transforms "downstream" IT innovations (Lyytinen and Rose 2003b).[5]

Innovations in *ways* to envision, design, and implement software by SFs are termed *process innovations*. Unlike base innovation, process innovations can be either internally generated or externally adopted. Examples of externally sourced innovations are situations where an SF adopts design principles or "best practices" created by others. Several examples of interally sourced innovations have been identified in the IS literature as SFs often modify their methods due to "learning by doing," or "learning by trying" (i.e., experimenting and diffusing them throughout the firm) (Mustonen-Ollila and Lyytinen 2003, 2004; Swanson 1994). Regardless of the source, process innovation involves the assimilation and deployment of knowledge to create services with a new process. There are significant incentives for SFs to engage in such activities in that they improve process effectiveness and efficiency. Consequently, process innovations involve any sort of change in software development processes including integration of new knowledge about how to manage requirements, apply design principles (e.g., abstraction), or use computer support (e.g., CASE tools, a.k.a., base innovation) (Fichman and Kemerer 1997; Messerschmitt and Szyperski 2003). Process innovations can also integrate new principles of software economics, of organizational coordination, of learning, or of control (Lyytinen and Rose 2003b; Mustonen-Ollila and Lyytinen 2003, 2004). Overall, process innovations cover both techical and administrative innovations (Lyytinen and Rose 2003b; Mustonen-Ollila and Lyytinen 2003, 2004; Swanson 1994). Process innovations are radical when they involve significant departures from existing ways to deliver software, thus engendering substan-

[3]We prefer to use the term *service* instead of *applications* because applications are commonly viewed in modern software vocabulary as a set of subservices that are dynamically composed from lower-level modular software.

[4]We do not deny the possibility that base innovations can be *created* internally by an SF. Our study, however, recognizes that such situations are uncommon. Therefore, we do not study them empirically. The rationale for excluding this possibility emerged from a review of the base innovations identified during our instrument development (see Appendix B). Sources for these base innovations are widely known. Readers can refer to Appendix C for the base innovation items included in the study. Innovation sources for these innovations are (1) narrowly focused research institutions (e.g., CERN); (2) large multinational software firms (e.g., Sun and Microsoft); and (3) multinational standards consortia (e.g., OMG and W3C). The SSFs in our sample and pilot study did not fall into any of these three types. Finally, the 19 IT experts in our pilot interviews were unaware of any base innovations that had been produced by any SSFs, nor had any been known to be produced in the dozens of SSFs with whom the authors have had contact.

[5]Prior research suggests that it is important to recognize interdependencies among different innovation types (Carlo et al. 2005, 2011; Mustonen-Ollila and Lyytinen 2003, 2004; Swanson 1994). Our final model reflects such relationships by including other innovation types as controls.

tial changes in process organization, design goals, technologies, or the type and number of actors.

Service innovation involves the adoption and use of knowledge to create new software functionality[6] for a client's tasks. As with process innovation, the genesis for service innovation can be either internal or external. Examples of externally sourced service innovations include application design concepts and frameworks found in books, training seminars, upstream vendors, or through imitation of avilable software services (Lyytinen and Rose 2003a). Internally sourced service innovations emerge when an SF innovates through learning by doing, trying, or experimenting (often with the new available base capability) (Messerschmitt and Szyperski 2003; Swanson 1994). Overall, service innovations integrate (1) knowledge about software domains, computing, and design principles (e.g., modularization), economics, coordination and business processes, user psychology and experience, and organizational structure and control with (2) an understanding of what one can do with existing base technologies (Messerschmitt and Szyperski 2003). SFs have strong incentives to engage in service innovation as it attracts new customers, opens new markets, and creates new sales opportunities. Service innovations are radical when they involve significant departures from existing software in terms of domains, functionality and structure, types of users or use goals, use processes, or the underlying business model.

Absorptive Capacity and Innovation

Multiple generic factors have been found to influence a firm's propensity to innovate including its task, environmental volatility, organizational munificence, size, slack, structure, culture, and leadership (Damanpour 1991; Subramanian and Nilakanta 1996; Wilson et al. 1999). However, in order to build a knowledge-based model of radical innovation, articulation of the content and structure of an SF's knowledge endowments is needed. As noted, for this task the concept of absorptive capacity (ACAP) is adopted and is defined as an SF's ability to identify, acquire, integrate, and exploit software related knowledge for commercial ends (Cohen and Levinthal 1989, 1990; Lane et al. 2006; Zahra and George 2002).[7]

The Epistemic and Behavioral Dimensions of Absorptive Capacity

Past research distinguishes between epistemic and behavioral dimensions of ACAP (Lane et al. 2006; Liao et al. 2007; Minbaeva et al. 2003; Roberts et al. 2011).[8] The *epistemic dimension* denotes what a firm "knows" (a.k.a., its *knowledge base*) consisting of both explicit and implicit facts, beliefs, ideas, conceptual structures, and frames that a firm's members possess. ACAP's *behavioral dimension* defines what the firm "does" (a.k.a., its *routines*) in relation to its knowledge. Within these two dimensions, we derive five knowledge factors.[9]

From a resource-based view, the epistemic dimension forms part of a firm's intangible and human resources (Bharadwaj et al. 1999; Pavlou and El Sawy 2006). It is path-dependent and a function of a firm's prior knowledge investments and experience (Cohen and Levinthal 1990; Todorova and Durisin 2007). The epistemic dimension is critical for absorbing new knowledge because "a firm without a prior technological knowledge base in a particular field may not be able to acquire one readily" (Cohen and Levinthal 1990, p. 138). A firm's epistemic dimension influences how effectively it acquires, integrates, and exploits new knowledge (Cohen and

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[6]Innovation is always defined from the perspective of the adopting unit (Zaltman et al. 1973). Service innovation takes place within an SSF when it adopts and uses knowledge to create an artifact unlike the ones *they* have previously built. It need not be new to the market or the client.

[7]Prior research defines absorptive capacity in multiple ways (see Cohen and Levinthal 1990; Grant 1996; Lane et al 2006; Todorova and Durisin 2007; Van Den Bosch et al. 1999). Our definition is a pragmatic synthesis of the main facets of the concept: (1) the unit of analysis is organizational units; (2) ACAP is distributed; (3) ACAP consists of epistemic and behavioral components; (4) the epistemic and behavioral components are path dependent; (5) the epistemic component describes what an organization knows; and (6) the behavioral component includes routines for knowledge acquisition, integration, and exploitation (see also Roberts et al. 2011).

[8]Alhough Cohen and Levinthal (1990) recognize the role of *both* knowledge factors (e.g., diversity) *and* routines in contributing to ACAP, most research defines ACAP *either* in epistemic *or* behavioral terms (Lane et al. 2006). Some studies (Liao et al. 2007; Minbaeva et al. 2003) have conceptualized ACAP as an individual's knowledge stock. Only 3.8% of all published research on ACAP views it both in epistemic and behavioral dimensions (Lane et al. 2006).

[9]Since no consensus has been reached as to what constitutes the epistemic and the behavioral dimension, we synthesized knowledge base and routine factors by surveying prior studies. Both ABI Inform and Google Scholar were used to search for salient factors using the key words: radical innovation, radical products, disruptive innovation, disruptive products, really new innovations, really new products, discontinuous innovation, and discontinuous products. We found nine articles that distinguished knowledge factors related to radical innovation. We also used key words absorptive capacity and innovation and found 15 additional articles. Among the 24 articles, 15 articles identified in total 11 knowledge constructs, which could be somehow related to absorptive capacity. We divided them into constructs that characterize an organization's epistemic dimension, and constructs that characterize its behavioral dimension. After removing overlaps, we concluded with five separate constructs.

Levinthal 1990; Grant 1996; Lane 2006; Todorova and Durisin 2007; Van Den Bosch et al. 1999). Within this dimension, we distinguish three factors: (1) knowledge diversity (Dewar and Dutton 1986); (2) knowledge depth (Ettlie et al. 1984); and (3) knowledge linkages (Damanpour 1991). The first two factors constitute "inward-looking" elements of a firm's knowledge base as they are defined by the organization's boundaries and governed by shared norms and firm-specific experience (Grant 1996). In contrast, knowledge linkages are "outward-looking," relational elements interfacing the organization and its environment (Cohen and Levinthal 1990, p. 133).

Knowledge diversity denotes the heterogeneity of technologies and application domains in which the SF has gained experience (Cohen and Levinthal 1990). An SF's knowledge diversity reflects the level of heterogeneity within its relevant knowledge base (i.e., the extent to which it covers distinct and unique knowledge elements that influence its task execution). *Knowledge depth* signifies the relative quality and level of detail that a firm can leverage for distinct knowledge elements in its knowledge base (Damanpour 1991; Dewar and Dutton 1986; Ettlie et al. 1984). Accordingly, a SF's knowledge depth is defined by the quality or expedience of its "at-hand" expertise for its distinct knowledge elements, measured comparatively against "typical" expertise found in the marketplace. Finally, *knowledge linkages* are defined as the breadth, reach, and intensity of channels through which knowledge can be externally identified and assimilated (Cohen and Levinthal 1990; Damanpour 1991; Fabrizio 2009). According to Cohen and Levinthal (1999), such "prospective 'receptors' to the environment" (p. 132) are critical for firms to innovate during rapid and uncertain technical change. As an outward-oriented element, knowledge linkages have often been called the "knowing-who" element of a firm's knowledge base. Typically, a SF's knowledge linkages consist of its relationships with external vendors, lead-user clients, technology "gurus," and research universities and laboratories.

The *behavioral dimension* of ACAP largely determines the effort, expediency, and variance of responses that a firm exhibits toward its knowledge-related stimuli (Cohen and Levinthal 1990, p. 131; Kim 1998). It consists of routines, "repetitive, recognizable pattern[s] of interdependent actions, involving multiple actors" (Feldman and Pentland 2003, p. 96). These routines form "internal mechanisms that influence the organization's absorptive capacity" (Cohen and Levinthal 1990, p. 135), and express "habitual" ways in which a firm responds to stimuli (Todorova and Durisin 2007). Hence, a firm's routines influence how effectively it can identify, acquire, integrate, and exploit knowledge given its current knowledge base.

Following Zahra and George (2002), we divide the behavioral dimension of ACAP into two factors: *sensing* and *experimentation routines*. *Sensing routines* affect how firms acquire external knowledge through scanning and focused searches, through seeking to understand its value through interpretation, and through assimilating it by integrating it into its knowledge structure (Cohen and Levinthal 1990; Grant 1996; Huber 1991). Searches allow firms to identify new technologies while their interpretations lead to assessment of their business value (Huber 1991; Srinivasan et al. 2002). Zahra and George call this factor *potential ACAP* (PACAP) in that it determines what knowledge elements in the firm's environment constitute a potential to be identified and assimilated. Sensing routines can guide an SF to periodically monitor developments in technology and business via scanning the press, or via observation while consulting. Mustonen-Ollila and Lyytinen (2004, pp. 42-43) illustrate a SF's sensing routines as follows:

> They would periodically scan their environment triggered by a critical incident (e.g., the emergence of information about new technology, a failure, etc.) or a periodic routine. Such scans normally went rapidly through their immediate environment by pooling knowledge related to [innovations] from several sources, including "friendly" consulting houses and major computer vendors.

The second factor of ACAP routines is *experimentation,* which Huber (1991, p. 91) defines as a way to "to increase the accuracy of feedback about cause–effect relationships between organizational actions and outcomes." Experiments integrate, transform, and evaluate the efficacy of assimilated knowledge in new contexts (Brown and Eisenhardt 1997, 1998; Eisenhardt and Martin 2000; Koberg et al. 2003). It consists of scripts for keeping organization in a state of change by trying out technologies, applications, business models, or organizational processes (Brown and Eisenhardt 1997, 1998; Eisenhardt and Martin 2000; Huber 1991). This factor constitutes what Zahra and George call *realized ACAP* (RACAP). In the end, RACAP determines the quality, range, and liquidity of knowledge the firm has on-hand for pursuing innovating for commercial ends. Experimentation draws upon abstract knowledge created by sensing and/or internal learning as reflected in the firm's knowledge base. It unpacks this knowledge and deconstructs or reconstructs it by recontextualizing, refining, and making it operational. Experimenters engage in "highly experiential and fragile processes with unpredictable outcomes" (Eisenhardt and Martin 2000, p. 1105) and generate novel associations through experience. Mustonen-Ollila and Lyytinen (2004) observed that experimentation critically affected an SF's process innovations: "most [innovations] could only be made useful after consid-

Table 1. Knowledge Factors Underlying Absorptive Capacity Affecting Radical Innovation

Factors	Definition	Direction of Impact on Innovation	Prior Studies Where Demonstrated
Epistemic Dimension: Knowledge Base			
Knowledge Diversity	The degree of heterogeneity of knowledge related to base and IT services	(+)[a]	Dewar and Dutton 1986 Fichman and Kemerer 1997 Grover et al. 2007 Germain 1996
Knowledge Depth	The depth and quality of expertise in base and IT services	(+)	Damanpour 1991 Dewar and Dutton 1986 Ettlie et al. 1984 Fichman and Kemerer 1997 Grover et al. 2007
Knowledge Linkages	The scope and intensity of an SSF's channels to external actors with critical knowledge related to IT innovation	(+)	Cohen and Levinthal 1990 Damanpour 1991 Nilikanta and Scamell 1990
Behavioral Dimension: Routines			
Sensing	An SSF's capability to sense its environment and assimilate knowledge related to new technical opportunities	(+)	Grover et al. 2007 Mustonen-Ollila and Lyytinen 2003a Srinivasan et al. 2002
Experimentation	The degree of an SSF's engagement in trial and error learning leading to transformation and exploitation of new knowledge	(+)	Brown and Eisenhardt 1997, 1998 Koberg et al. 2003 Mustonen-Ollila and Lyytinen 2003a West and Iansiti 2003

[a]+ = positive impact

erable adaptation where the 'available' solution was fitted with a unique problem" (p. 43). Table 1 summarizes each knowledge factor and its reported influence on radical innovation.

A Mediated Structure of Absorptive Capacity

In line with Roberts et al. (2011), we posit that the two dimensions of ACAP are interrelated and form an emergent property: they build upon each other to *jointly* enhance a firm's capability to innovate. Consequently, we postulate that firms need to organize the five knowledge factors in a specific way that is most conducive for future innovation, where the routine factors are viewed to *mediate* the impact of the knowledge base factors upon innovation (Cohen and Levinthal 1990; Roberts et al. 2011; Zahra and George 2002). In this configuration, routines act as mediators because they determine (1) how much and what type of *new* knowledge can be acquired and assimilated given a firm's existing knowledge base, and (2) the extent to which this knowledge can be integrated, transformed, and exploited to yield new innovations. Essentially, the routines intervene by transmitting the positive effect of the knowledge base (i.e., knowledge diversity, knowledge depth, and knowledge linkages) on the level of innovation (Mathieu and Taylor 2006). Consequently, the impact of the firm's knowledge base is distal, while the effect of routines is direct and proximal.

This mediated reading of ACAP suggests that different sorts of knowledge endowments influence the firm's level of innovation in distinct ways: each activates a distinct configuration of ACAP elements within a causal path leading to innovation. The causal logic for this sequence is explained as follows. A firm's knowledge base factors indirectly affect the level of innovation *through sensing*. This takes place for three reasons. First, sensing is about the search for new knowledge from the environment, whereas knowledge already internalized does not need to be sought out. Therefore, whatever new knowledge is acquired through sensing should logically be externally sourced. Second, what a firm already knows (reflected in its knowledge diversity and knowledge depth) affects what it will search for. As Cohen and Levinthal (1990, p. 136) note, "the possession of related expertise will permit the firm to better understand and therefore evaluate the import of intermediate technological advances." Thus, knowledge diversity and knowledge depth precede and influence the level of sensing. Third, the strength of a firm's knowledge linkages (e.g., quality, number, etc.) will directly and positively affect the frequency and quality of the searches (Cohen and Levinthal 1990).

Next in the sequence, sensing routines positively affect experimentation. Prior research has examined antecedents to experimentation such as research and development spending (West and Iansiti 2003), normative values and rewards (Lee et al. 2004), organizational forms (Qian et al. 2006), experimentation strategies (Thomke 1998; Van Dyck and Allen 2006), and the impact of new technologies (Thomke 1998; Thomke et al. 1998). However, no study has tested the relationships between knowledge base factors, sensing, and experimentation. We propose the following sequence: sensing leads to new knowledge, which invites higher levels of experimentation. As Cohen and Levinthal (1990) suggest, tacit innovation knowledge is acquired with experimentation (i.e., "only through experience within the firm," p. 135). By doing so, experimentation mediates the impact of sensing on innovation by generating new applicable ideas that can be diffused (Lane et al. 2006; Zahra and George 2002).[10] Accordingly, the impacts of a firm's knowledge endowments are transmitted in a sequence where improvements in the knowledge base lead to a higher level of sensing, which then positively influences the level of experimentation. Finally, higher-level experimentation increases the level of innovation (Figure 1). In addition, the impact between base factors and innovation is *fully mediated* (i.e., the innovation effect of base factors depends on and increases with the presence and increased level of sensing and experimentation).

External and Internal Paths of ACAP

Finally, our model addresses the impact of alternative sources of knowledge on innovation. Specifically, process and service innovations in SFs can simultaneously be the function of either or both internally or externally sourced knowledge. When the source of knowledge is solely internal, sensing is unnecessary as a prerequisite to experimentation. As a result, two paths of influence are distinguished reflecting both internally and externally sourced innovation: the *internal* and *external paths of influence in knowledge-based innovation* (Figure 2).

When SFs engage in externally sourced innovation that depends on extramural knowledge, they enact an *external path* through which they adopt and use external knowledge endemic to innovation (Cohen and Levinthal 1990; Fichman and Kemerer 1997; Lane et al. 2006; Mustonen-Ollila and Lyytinen 2003, 2004; Nilakanta and Scamell 1990). This path can be formulated as a three step, *two-mediator, external path* as shown with solid arrows in Figure 2. In this path, sensing and experimentation, *jointly and in this sequence*, mediate the impact of a firm's knowledge base on the level of innovation (Lane et al. 2006; Zahra and George 2002). In the external path, both sensing and experimentation can be allocated to dedicated units, which enact specialized routines for sensing and experimentation. Routines include market monitoring, visits to fairs or seminars for sensing, field trials, piloting, or development of prototypes for experimenting. Accordingly, the external path can be formulated as follows: Knowledge base → Sensing → Experimentation → Innovation.

In contrast, when internally inventing services or processes, SFs need to innovate via an internal path. This path was observed by Mustonen-Ollila and Lyytinen (2004) when they noted, "to our surprise, [software] organizations would, in most cases, turn to their internal exploration and utilize past experience and immediate resources" (p. 44). They also found that SFs drew upon recontextualized experience when trying out new knowledge combinations through *bricolage*. Other research on experimentation confirms the same: fresh experience plays a positive role in affecting R&D performance, because it influences the ways the organization frames its product designs (West and Iansiti 2003). Firms can thus forego sensing by recombining and recontextualizing their acquired knowledge through expansion, diffusion, and recontextualizing, which generates new connections between the acquired knowledge and their environmental needs (Damanpour 1991; Dewar and Dutton 1986; Ettlie et al. 1984). This happens through mechanisms such as local spill-overs, moving people or artifacts around, or using some people as envoys to speed up learning. Accordingly, we postulate a two-step, *one-mediator, internal path of influence*. Through experimentation, an SF transforms and recontextualizes its accumulated internal knowledge: knowledge diversity and depth positively influence the level of innovation (dotted paths in Figure 2).[11] Within the internal path we exclude knowledge linkages as they are focused on "outward" looking elements of the firm's knowledge base. Accordingly, an SF's accumulated knowledge (captured in knowledge depth and knowledge diversity) directly influences its experimentation:

[10]Zahra and George hint at the mediated nature of ACAP by characterizing its two components as distinct combinative and complementary, and temporally separate (see their Figure 1). Nowhere does their discussion explicitly formulate the constructs as a mediated structure (see also Lane et al 2006; Todorova and Drusin 2007).

[11]The internal path has not been typically defined as part of ACAP, but is consistent with the claims that RACAP precedes and directly drives innovation.

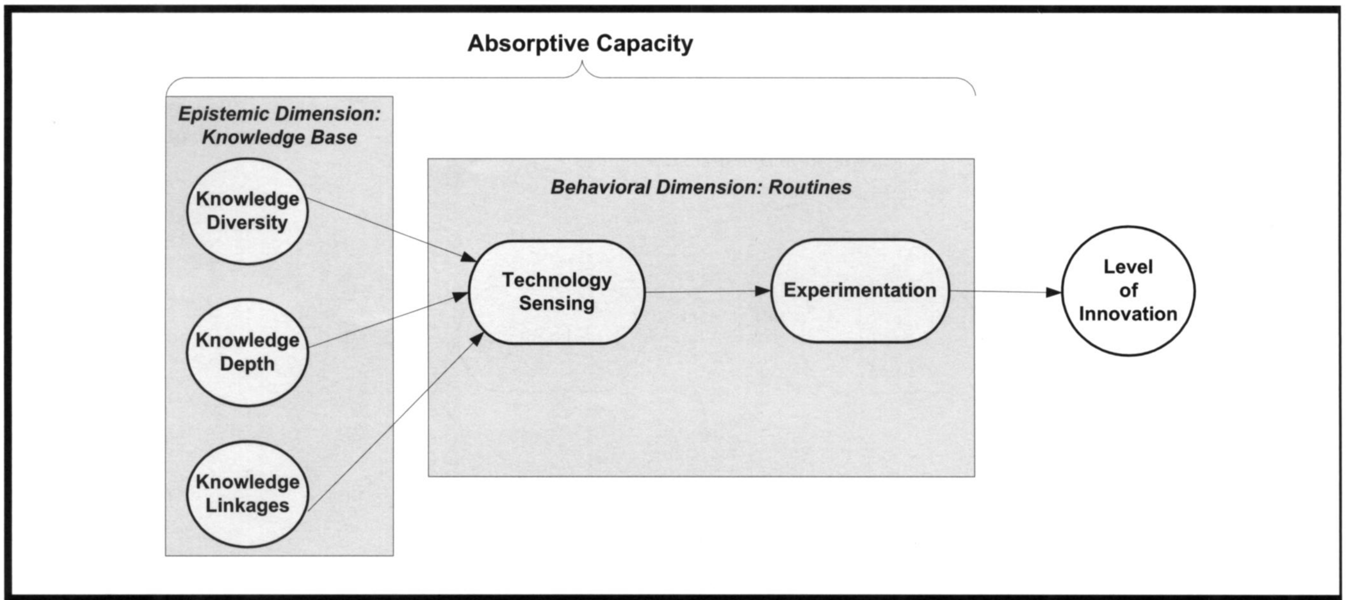


Figure 1. A Mediated Model of ACAP and Innovation

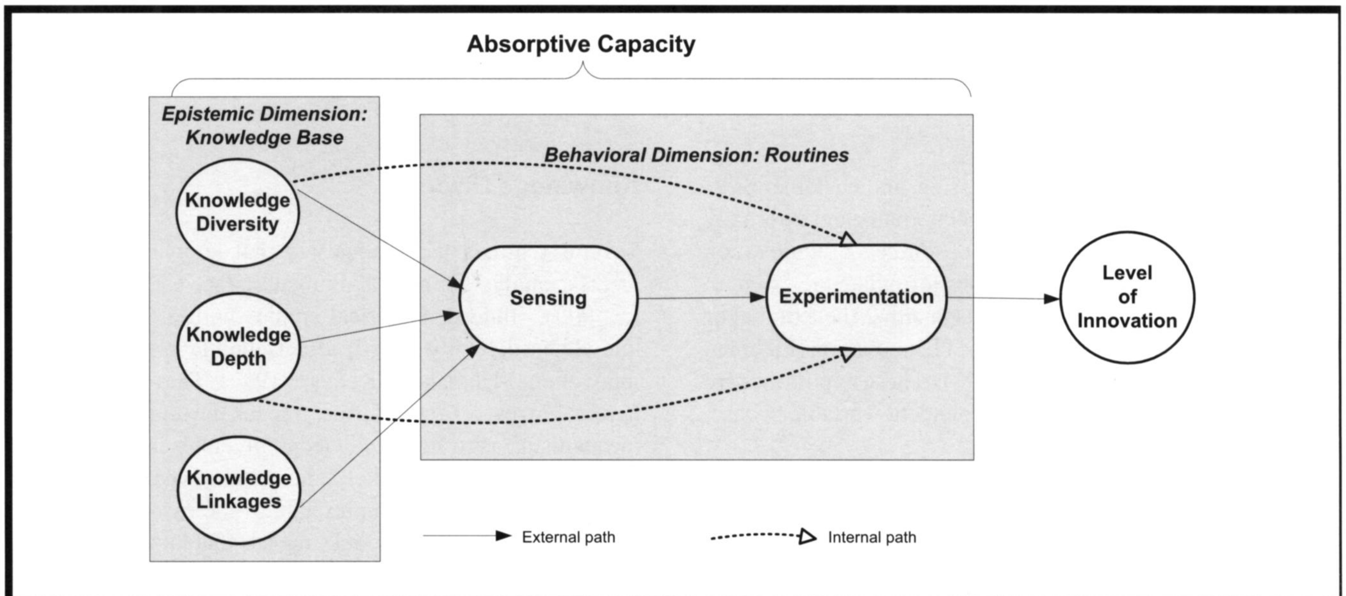


Figure 2. External and Internal Paths of Influence in Knowledge-Based Innovation

knowledge diversity broadens frames and increases options for experimentation, while knowledge depth increases the level of experimentation and its efficiency. Experimentation, in turn, increases a firm's level of innovation by generating new knowledge. This suggests two fully mediated internal paths: Knowledge diversity → Experimentation → Innovation; and Knowledge depth → Experimentation → Innovation (Figure 2).

A Knowledge Model of Radical IT Innovation in Software Firms

This section formulates the knowledge-based model in terms of (1) dependent variables (three innovation types); (2) mediators (two routine factors); (3) independent variables (three knowledge base factors); and (4) controls (prior IT innovation

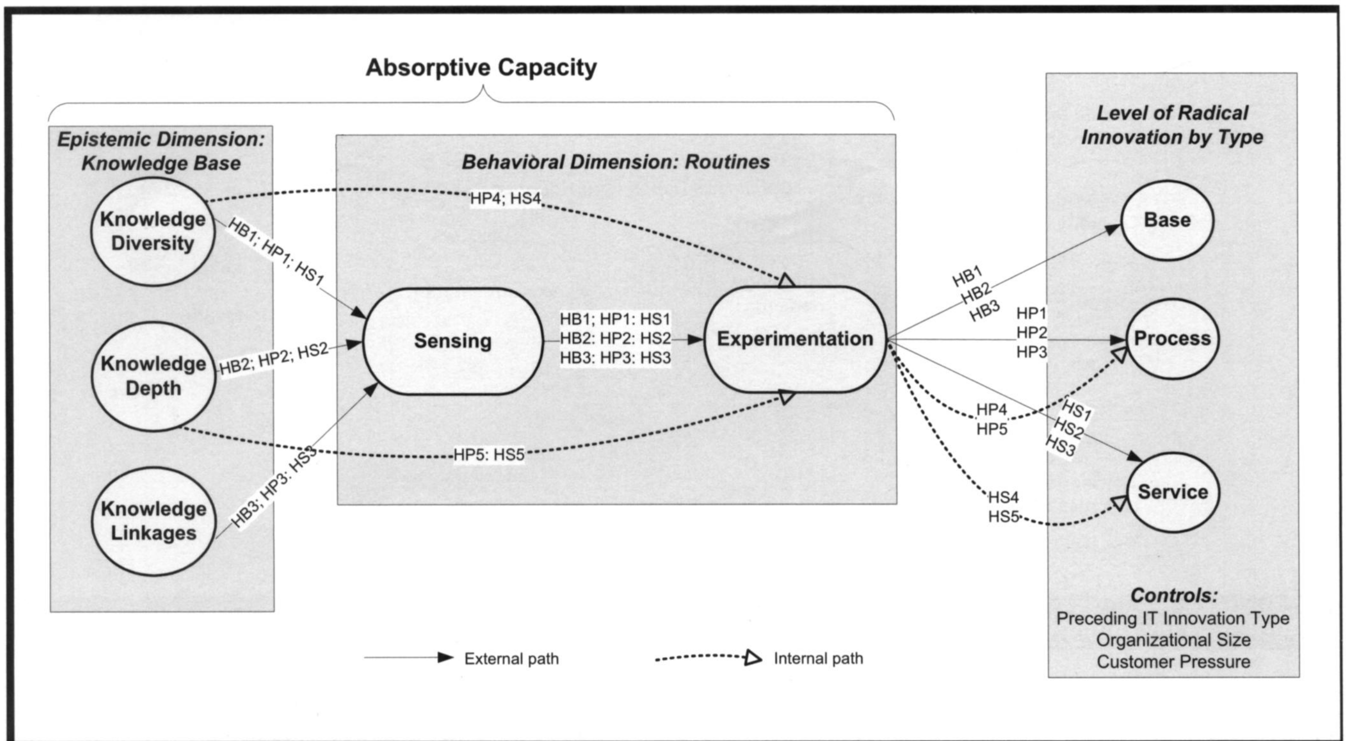


Figure 3. A Mediated Knowledge-Based Model of Radical IT Innovation

types reflecting the role of ecology, size, and customer pressure) (Figure 3). The model includes internally and externally mediated paths, reflecting the two sources of innovation knowledge. Accordingly, hypotheses formulate the extent to which each knowledge base factor (via either the external or the internal path) affects each type of IT innovation (Fichman and Kemerer 1997; Grover et al. 1997). These hypotheses are articulated in the order of the dependent variable: base, process, and service innovation.

Explaining Base Innovation

As noted, radical base innovations reach SFs *only* through an external path: Knowledge base → Sensing → Experimenting → Base innovation.[12] In other words, increases in the knowledge base factors will increase the level of sensing and then experimenting, ultimately increasing the level of base innovation.

[12]As noted, we do not deny the possibility of an internal path, but especially for SSFs such an engagement is highly unlikely. Our studies have not identified a single SSF that has done this, although we always offered subjects the possibility to list such engagements.

Knowledge Diversity

Several scholars have suggested that knowledge diversity forms a catalyst for radical innovation (see e.g., Shenkar and Li 1999). Indeed, empirical studies within SFs show that knowledge diversity directly affects their level of radical base innovation (Fichman and Kemerer 1997). The research model herein, however, tries to further unpack the underlying causal mechanisms as to how knowledge diversity impacts radical base innovation. Most likely, the cumulative path of knowledge effects is more complex due to the external nature of base innovations. Our model suggests that knowledge diversity promotes base innovation primarily through sensing and experimentation. Five reasons can be offered to account for this. First, a higher level of diversity increases opportunities to create novel linkages within the existing knowledge base, triggering searches for new technology and thus increasing sensing levels (Cohen and Levinthal 1990; Kogut and Zander 1992). Second, diversity increases the likelihood that the identified knowledge is related to what is already known and the knowledge is easier to assimilate during sensing (Cohen and Levinthal 1990). Third, radical base innovations are imbued with uncertainty about their future value. They are thus difficult to integrate with existing knowledge elements (Rosenberg 1990). Such uncertainty can be alleviated by increased knowledge diversity that brings additional perspectives to evaluate garnered knowledge and increase the level of sensing. Fourth, knowledge diversity creates requisite variety to interpret and contextualize the knowledge for further innovation deployment and subsequently increases experimentation (Cohen and Levinthal 1990). Finally, the deployment of radical base innovations (i.e., their integration and institutionalization) is better promoted by multiple loosely related knowledge domains, thus increasing the level of experimentation (Ahuja and Katila 2001; Lane et al. 2006).

HB1 (Knowledge diversity → Sensing → Experimentation → Base innovation): Knowledge diversity influences positively the level of sensing and experimentation, which influences positively the level of base innovation. Knowledge diversity will not directly influence base innovation.[13]

Knowledge Depth

Prior studies show that a firm's knowledge depth directly and positively affects radical innovation (Dewar and Dutton 1986; Ettlie et al. 1984; Grover et al. 2007). Fichman and Kemerer (1997) also demonstrated that this holds for SFs with their base innovation. In contrast, we suggest that knowledge depth affects radical base innovation only indirectly through sensing and experimentation. At least five reasons can account for this. First, experts "deep in the know" can more fluently follow and understand technological developments, and, therefore, will sense more external knowledge. Second, experts often experience intense group pressure to identify new technologies, creating a significant extrinsic motivator for sensing. Third, due to their deeply contextualized knowledge, firms with higher knowledge depth can assimilate new knowledge more easily. This also promotes increased experimentation. Fourth, assimilated deep technical know-how is "sticky," enabling highly ambiguous base-innovation knowledge to be more easily contextualized, which leads to higher experimentation (Dewar and Dutton 1986; von Hippel 1994). Finally, high-level experts are better equipped to recontextualize assimilated knowledge and thus appreciate its potential value.

HB2 (Knowledge depth → Sensing → Experimentation → Base innovation): Knowledge depth influences positively the level of sensing and experimentation, which influences positively the level of base innovation. Knowledge depth will not directly influence base innovation.

Knowledge Linkages

In general, radical innovations dissolve current technological trajectories (Dosi 1982), and render prevailing technology knowledge irrelevant (Teece 1998). Therefore, during periods of radical innovation, firms need to constantly search externally for complementary knowledge (Nicholls-Nixon and Woo 2003; Warner 2003). The success of external searches, in turn, will depend on the scope and intensity of a firm's environmental linkages (Damanpour 1991). Not surprisingly, several studies have shown that increased external linkages have a direct positive influence on the level of radical innovation (Arora and Gambardella 1994; Cockburn and Henderson 1998; Cohen and Levinthal 1990; Fabrizio 2009 Tushman and Anderson 1986). Nilakanta and Scamell (1990) also found that internal IT units with more knowledge linkages engage in more radical base-innovation. In contrast, a mediated path is proposed here and postulates that higher levels of knowledge linkages (i.e., the more and better connections an SF has with vendors, lead clients, and research institutions) leads to higher levels of sensing and experimentation which finally increases base innovation levels.

HB3 (Knowledge linkages → Sensing → Experimentation → Base innovation): Knowledge linkages positively influence the level of sensing and experimentation, which influences positively the level of base innovation. Knowledge linkages will not directly influence base innovation.

Explaining Process Innovation

Unlike base innovation, SFs innovate radically with processes via either external or internal paths. At the same time, radical process innovations are difficult to implement due to cognitive bias, habitualization, and high uncertainty (Fichman and Kemerer 1997, Mustonen-Ollila and Lyytinen 2003). Prior studies have observed direct and positive effects of knowl-

[13]This presumes a full mediation in the complete three step path (i.e., either complete or distal mediation, implying that the "mediators" fully transmit the effect of the "first" antecedent). Accordingly, we do not allow for the path Knowledge diversity → Base innovation, suggesting partial mediation. Overall, this fully mediated model also meets the requirements of temporal precedence and theoretical justification (Mathieu and Taylor 2006; Shrout and Bolger 2002). Note that this interpretation allows for *either* full *or* partial mediation in the path Knowledge diversity → Sensing → Experimentation and the presence of both Knowledge diversity → Sensing → Experimentation, and Knowledge diversity → Experimentation are possible. As these paths are not of primary theoretical interest they will not be hypothesized here. Similar interpretation applies to all similar hypotheses related to external paths.

edge diversity (Dewar and Dutton 1986; Fichman and Kemerer 1997; Germain 1996) and knowledge depth (Dewar and Dutton 1986; Fichman and Kemerer 1997) in promoting radical process innovation. Ettlie et al. (1984) observed that knowledge depth positively and indirectly impacted process innovation through technology–organization congruence. In contrast, a mediated influence of a firm's knowledge base upon its radical process innovation should be found both because of the external source of some innovation and the necessity to have present mediating behaviors that transfer internal new knowledge to process changes.

In the case of the external path, the following propositions are suggested for process innovations. First, as an SF's knowledge diversity increases, its knowledge domains and their interactions lead to a larger number of searches for process knowledge. The increased amount of assimilated process knowledge will increase the level of experimentation leading to more process innovations. Second, as an SF's knowledge depth increases, the firm's knowledge domains and expertise deepen, leading to a larger number of searches for new process knowledge. This will increase the amount of process knowledge and the level of experimentation leading to more process innovations. Third, as an SF's knowledge linkages increase, the scope of knowledge searches widen, increasing the likelihood of obtaining new process knowledge. This leads to higher levels of experimentation, yielding more process innovations.

HP1 (Knowledge diversity → Sensing → Experimentation → Process innovation): Knowledge diversity influences positively the level of sensing and experimentation, which influences positively the level of process innovation. Knowledge diversity will not directly influence process innovation.[14]

HP2 (Knowledge depth → Sensing → Experimentation → Process innovation): Knowledge depth influences positively the level of sensing and experimentation, which influences positively the level of process innovation. Knowledge depth will not directly influence process innovation.

HP3 (Knowledge linkages → Sensing → Experimentation → Process innovation): Knowledge linkages positively influence the level of sensing and experimentation, which influences positively the level of process innovation. Knowledge linkages will not directly influence process innovation.

With regard to the internal path, higher levels of knowledge diversity provide a larger number of knowledge items and item combinations that invite more ways to try out new processes. Likewise, higher levels of expertise offer more refined knowledge structures, which invite more ways to try out new processes. Experts are also better equipped in recontextualizing the knowledge and trying out new process arrangements leading to higher levels of experimentation, which leads to higher levels of process innovation.

HP4 (Knowledge diversity → Experimentation → Process innovation): Knowledge diversity influences positively the level of experimentation, which influences positively the level of process innovation. Knowledge diversity will not directly influence process innovation.

HP5 (Knowledge depth → Experimentation → Process innovation): Knowledge depth influences positively the level of experimentation, which influences positively the level of process innovation. Knowledge depth will not directly influence process innovation.

Explaining Service Innovation

SFs can engage in service innovation via both external and internal paths. Therefore, not surprisingly, prior research shows that knowledge diversity, knowledge depth, sensing and experimentation positively and directly influence the level of service innovation (Grover et al. 2007; Srinivasan et al. 2002). Grover et al. (2007) also observed that the influence of knowledge specialists (i.e., knowledge depth) was intervened by technology–organization congruence, and the impact of environmental scanning (e.g., sensing) was transmitted through technology–organization congruence and IS power. SFs can thus externally *adopt* service innovations by imitating observable applications in their environment (Cohen and Levinthal 1990). This paper postulates the presence of mediated structures—both for internal and external paths.

[14]In the case of the presence of both externally adopted or internally generated innovation, all significant paths along Knowledge diversity → Sensing → Experimentation → Process innovation are interpreted as external paths. The presence of a path Knowledge diversity → Experimentation → Process innovation can instead be due to the fact that sensing partially mediates the impact of knowledge diversity upon experimentation when the external path is present and form thus one alternative "path" of the whole external path, or it expresses that the process innovation was internally created and the path presents a true internal path. If the presence of only an internal path were detected, then the latter interpretation holds. If an external path is also detected, it would be interpreted as the presence of *both* impacts (partial mediation in the external path and an internal path). The presence of all internal paths will be interpreted similarly.

In the case of the external path, the following can be observed. First, as an SF's knowledge diversity increases, it has access to more diverse knowledge domains and their interactions. This leads to a larger number of searches for domain and application knowledge. The higher levels of domain and application knowledge would increase the level of experimentation leading to more service innovations. Second, as an SF's knowledge base deepens, its knowledge about domains and applications becomes more refined, leading to a larger number of searches for application knowledge. This new application knowledge would increase the level of experimentation leading to more service innovations. Third, as an SF's knowledge linkages increase, it widens the scope of knowledge searches, which increases the likelihood of new combinative knowledge. This leads to higher levels of experimentation, resulting in more service innovations.

HS1 (Knowledge diversity → Sensing → Experimentation → Service innovation): Knowledge diversity influences positively the level of sensing and experimentation, which influences positively the level of service innovation. Knowledge diversity will not directly influence service innovation.

HS2 (Knowledge depth → Sensing → Experimentation → Service innovation): Knowledge depth influences positively the level of sensing and experimentation, which influences positively the level of service innovation. Knowledge depth will not directly influence service innovation.

HS3 (Knowledge linkages → Sensing → Experimentation → Service innovation): Knowledge linkages positively influence the level of sensing and experimentation, which influences the level of service innovation. Knowledge linkages will not directly influence service innovation.

SFs can also *internally* generate radical service innovations (Lyytinen and Rose 2003b; Swanson 1994) when they combine their domain and application knowledge in new ways and reapply them. This corresponds with West and Iansiti's (2003) and Thomke's (1998) findings that an organization's internal knowledge and experimentation correlate positively (and directly) with its R&D performance. Simply, higher levels of knowledge diversity generate more combinations and their interpretations, leading to new application ideas, leading to higher levels of experimentation. Likewise, firms with deeper knowledge will be better equipped to value and recontextualize the technological and domain knowledge, leading to higher levels of experimentation. More experimentation, in turn, leads to higher levels of service innovation. Therefore, we propose

HS4 (Knowledge diversity → Experimentation → Service innovation): Knowledge diversity influences positively the level of experimentation, which influences positively the level of service innovation. Knowledge diversity will not directly influence service innovation.

HS5 (Knowledge depth → Experimentation → Service innovation): Knowledge depth influences positively the level of experimentation, which influences positively the level of service innovation. Knowledge depth will not directly influence service innovation.

Controls and Manipulation Checks

As shown in Figure 3, we include type of IT innovation and its order effects (Carlo et al. 2011; Swanson 1994), organizational size, and customer pressure as controls. With regard to order effects, we observe the effect of a dominating sequence in which the three IT innovation types are adopted (Carlo et al. 2011). In a sense, prior IT innovations can be viewed as environmental opportunities, constraints, or new knowledge elements that affect subsequent innovation (Lyytinen and Rose 2003b; Messerschmitt and Szyperski 2003). Accordingly, base innovation precedes service innovation, and they both precede process innovation, while the level of each preceding innovation type impacts the level of the subsequent type of IT innovation (Carlo et al. 2011; Swanson 1994). In line with this, we introduce the level of radical *base innovation* as control (positive) for radical service innovation, and the level of radical *base* and *service innovations* as controls (positive) for radical process innovation.

Earlier research indicates that *organizational size* can either positively or negatively influence radical innovation (Damanpour 1992). On one hand, large firms are better positioned to innovate radically as they are more diversified, have more slack (Ettlie et al. 1984; Grover et al. 2007), and can more easily buffer against financial risks and amortize learning costs (Fichman and Kemerer 1997). On the other hand, larger firms face higher learning barriers when innovating radically (Christensen 1997) due to their high levels of formalization, complexity, and structural inertia (Damanpour 1992; Grover et al. 2007). Without hypothesizing the potential direction of its impact, we include size as a control.

Institutional theory (DiMaggio and Powell 1983; Meyer and Rowan 1977) identifies three institutional pressures shaping the organization's responses to innovations: mimetic, coercive, and normative (Loh and Venkatraman 1992; Newell et al. 2000; Teo et al. 2003; Wang and Ramiller 2004). Among SFs, mimetic and normative pressures associated with base and service innovation are expressed in customer pressure. Thus, we introduce *customer pressure* as another control. Finally, as we are studying *radical IT innovation* we include a *manipulation check* of perceived radicalness of each of the IT innovation type as a contextual variable.

Research Design and Methodology

To validate the proposed model, we conducted a survey among small SFs that were engaged in innovating with Internet computing. *Internet computing* was selected for three reasons. It was (1) a radical innovation (see Appendix A), (2) analytically and empirically validated to trigger radical innovation among SSFs across all three innovation types (Lyytinen and Rose 2003a), and (3) a recent enough phenomenon at the time of data collection to minimize hindsight and recall bias. *SSFs* were selected for three primary reasons. First, the SEM-based analysis method adopted required a sufficiently large sample size, which was easier to achieve with SSFs. Second, the theoretical model best fit software organizations that developed tailored software products for external clients (i.e., SSFs). Finally, two U.S.-based software associations offered the researchers access to conduct surveys among their member organizations (e.g., use of their logos, joint seminars, etc.), who almost exclusively employed no more than 100 people.

Survey Administration

Two rounds of paper-based surveys were sent to people with such titles as CEO, CIO, CTO, president, chairman, owner, principal or vice president of R&D of each company. These respondents were deemed to be the key decision makers in technology and market choices and most qualified in their company to speak about the firm's experience with Internet computing.

We received 139 completed surveys from the 710 member firms who developed software for external clients with an acceptable response rate (20 percent) given that our survey was voluntary and involved top management (Stimpert 1992).[15] Of the replying companies, 11 were omitted from our sample since they had between 132 and 75,000 employees and could not be viewed as *small*.[16] Our final sample included 121 valid responses from SSFs. Table 2 summarizes the sample characteristics. We also implemented several measures to improve *response accuracy* and minimize the threat of *nonrespondent bias* and *common method bias* (Appendix B).

Research Constructs

A survey instrument was generated through a five-year field study among SSFs (Lyytinen and Rose 2003a, 2003b), and an iterative review of radical innovation, absorptive capacity, and Internet computing literature.[17] Wherever possible, measurement items were based on existing scales. Their face and content validity were tested through a thorough pilot study. Appendix C explains the instrument validation process and lists the final constructs.

Dependent Variables

The criterion variable for each innovation type is the "level" of radical base, process, and service innovation, respectively. This is measured by the number of Internet computing innovations in each type *adopted and used* by the SSF (absolute scale). This indicates how extensively the firm had adopted radical innovations within each type during the study period (Lyytinen and Rose 2003b). Fichman (2001) argues that such aggregated measures are more robust and generalizable, promote stronger predictive validity, and reduce Type II errors.[18] To formulate this scale, we identified a pool of innovations associated with Internet computing in each type during the last 10 years based on a literature review and a pilot study with industry experts (Fichman and Kemerer 1997; Grover et al. 1997). The list of base innovations generated by the participants was, as noted above, exclusively a collection

[15]None of the experts who had helped us in developing the survey instrument were among the respondents.

[16]These 11 data points were eliminated for internal validity. First, 121 firms had fewer than100 people. Second, 11 are not enough to carry out multi-group comparisons. Finally, their very wide size ranges would likely bias our results.

[17]Over 65 versions were created during the pilot study to ensure the validity and the usefulness of the instrument.

[18]There are several threats to the validity of the measures including granularity (i.e., what counts as a separate innovation) and interpretation (i.e., what does each innovation really mean as the terminology is not fixed).

Table 2. Sample Characteristics (N = 121)

	Obs.	%
Number of Employees		
1–20	95	78.5
20–40	15	12.4
40–60	8	6.6
60–80	2	1.7
80–100	1	0.8
Total	**121**	
Respondent Title		
President, CEO, Partner, Principle, Owner, Managing Director, Executive VP	86	71.1
CIO/CTO/VP of IS, VP of Product Development	9	7.4
IS Manager, Technology Manager, Software Development Manager, Director	7	5.8
Other Managers in IS Department	2	1.7
Business Operations Manager, COO	3	2.5
Other VP (Marketing, Finance, etc.), CFO	7	5.8
Others	7	5.8

of externally generated innovations (see Appendix D).[19] Innovations in services and processes included only those that were judged by our panel of experts to be a result of using the aforementioned Internet base capabilities. Any innovations that were judged to have come into the "mainstream" independently of Internet computing were omitted. The process innovation construct covered both administrative and technological innovations (Swanson 1994), while base and service innovations contained only technological innovations. The final constructs consist of 10 base innovations, 8 process innovations, and 14 service innovations, offering large enough variance.

Independent Variables

The three factors constituting the knowledge base were conceptualized as formative constructs. *Knowledge diversity* was captured by modifying Fichman and Kemerer's (1997) three-item construct. Five items were used to represent diversity of: (1) system platforms; (2) database technologies; (3) application architectures; (4) programming languages; and (5) middleware. This construct measured the heterogeneity of the knowledge base across an SF's key technological areas. *Knowledge depth* measured the quality of the firm's critical technical expertise[20] and was identified by a firm's relative quality of technical expertise when compared to its peers in each of the five areas identified by the knowledge diversity construct. *Knowledge linkages* were captured by items that measured whether a firm had strong relationships with leading technology vendors, lead user clients, and research universities (Appendix C).

Mediators

We measured *sensing* by Srinivasan et al.'s (2002) reflective four-item construct, which tapped into the routines for detecting and understanding new technologies and related market opportunities. *Experimentation* was based on Brown and Eisenhardt's (1998, 2003) reflective five-item construct measuring whether a firm carries out experimental technology projects or is actively *trying out* new technologies and processes.[21] It does not distinguish whether the firm applies external or internal knowledge during the experimentation.[22]

[19]Respondents had the possibility to add other internally generated innovations for each type but none were noted for base innovations, increasing the validity of the measure used.

[20]We rejected earlier constructs such as the total number of technical personnel (Dewar and Dutton 1986) because these measures confound with knowledge diversity and size, and do not capture truly the level of technological expertise. For example, having 1,000 incompetent COBOL programmers does not make a firm deeper in its technological expertise, while a firm with 10 people who are leading programming language experts would.

[21]Two other items, "future-oriented strategic alliances" and "is a leader in adopting new technologies," were dropped during factor analysis from this construct due to low loadings.

[22]We thank one reviewer for pointing this out.

Table 3. Measurement Model: Factor Loadings, Reliability, and Convergent Validity

Construct (Reliability)	Indicator	Loadings	Convergent Validity (t-stat)
Sensing (0.83)	s1	0.80***	19.70
	s2	0.77***	14.42
	s3	0.78***	19.74
	s4	0.64***	6.36
Experimentation (0.97)	ex1	0.81***	18.19
	ex2	0.85***	24.28
	ex5	0.80***	12.76
Customer Pressure (0.84)	cp1	0.66***	5.21
	cp2	0.82***	14.99
	cp3	0.90***	55.93
Base Radicalness (0.90)	b_rad1	0.81***	18.95
	b_rad2	0.88***	28.15
	b_rad3	0.92***	57.36
Process Radicalness (0.89)	p_rad1	0.83***	15.17
	p_rad4	0.88***	41.81
	p_rad5	0.85***	17.55
Service Radicalness (0.92)	s_rad1	0.84***	20.44
	s_rad2	0.90***	39.71
	s-rad3	0.89***	46.01
	s_rad4	0.81***	18.14

*p < 0.10; **p < 0.05; ***p < 0.01. Insignificant items were dropped.

Control and Manipulation Variables

After Carlo et al. (2011), we introduced the level of *base* and *service* innovations as controls for process innovation, and the level of base innovation as a control for service innovation. Following Blau and McKinley (1979), we measured *organizational size* by the number of employees (log transformed). *Customer pressure* was adopted from Srinivasan et al. (2002). We customized Gatignon et al.'s (2002) reflective five-item construct to detect *perceived radicalness* of each innovation type.

Measurement Model and Manipulation Check

Since knowledge diversity, knowledge depth, and knowledge linkages are formative measures, we created their respective indices formulated as follows (Appendix C details the procedures to establish construct reliability and validity):

Knowledge Diversity = 0.533 × Knowledge Diversity in System Platforms + 0.435 × Knowledge Diversity in Database Technologies + 0.197 × Knowledge Diversity in Programming Languages + 0.203 × Knowledge Diversity in Middleware

Knowledge Depth = 0.293 × Knowledge Depth in System Platforms + 0.293 × Knowledge Depth in Database Technologies + 0.238 × Knowledge Depth in Application Architectures + 0.486 × Knowledge depth in Middleware

Knowledge Linkages = 0.443 × Relationship with Technology Vendors + 0.198 × Relationship with Clients + 0.4501 × Relationship with Research Universities.

For the latent, reflective constructs, we carried out an exploratory factor analysis (EFA) and a confirmatory factor analysis (CFA). Table 3 shows that all constructs have a *composite reliability* greater than 0.83, exceeding the cutoff of 0.70 (Straub 1989). The items have good internal consistency and are good indicators for their common latent construct. The significant standard loadings ($p < .01$) suggest good *convergent validity*. As shown in Table 4, the square root of the AVE (average variance extracted) for each construct is greater than the correlation of this construct to all other constructs, exhibiting good *discriminant validity* (Fornell and Larcker 1981). The analysis of common method variance is reported in Appendix F.

For the *manipulation check* we analyzed the respondents' ratings of perceived radicalness for each innovation type. Al-

Table 4. Correlations of Latent Variables (Diagonal SQRT of AVE)	Experimen-tation	Sensing	Customer Pressure	Base Radicalness	Process Radicalness	Service Radicalness
Experimentation	**0.82**					
Sensing	0.35***	**0.75**				
Customer Pressure	0.30***	0.16	**0.80**			
Base Radicalness	-0.07	0.15**	0.12	**0.87**		
Process Radicalness	0.34***	0.23**	0.25**	0.24**	**0.85**	
Service Radicalness	-0.08	0.10	0.30	0.63***	0.32***	**0.86**

*p < 0.10; **p < 0.05; ***p < 0.01.

though multiple studies have identified Internet computing to be radical (Lyytinen and Rose 2003a, 2003b; Srinivasan et al. 2002), a validation of the perceived radicalness was included as a precaution to guarantee that the context of the study was valid (i.e., test for *disconfirmation* if the studied innovations were radical). The average means of this measure ranged from 3.25 to 4.25 on a scale of 5, where 3 indicates agreement and a 5 indicates strong agreement with statements such as "these technologies were *breakthrough* innovations." Thus, the firms overwhelmingly perceived the innovations they adopted as radical and the reported level of high radicalness suggests that we were, in fact, investigating radical IT innovation.[23]

Hypotheses Testing

Since the hypotheses for external paths (HB1-3, HP1-3, HS1-3) suggest a two-mediator $X \rightarrow M_1 \rightarrow M_2 \rightarrow Y$ structure, we used Shrout and Bolger's (2002) and Fletcher's (2006) tests. The hypotheses for the internal paths (HP 4-5, HS 4-5) involve a one mediator $X \rightarrow M \rightarrow Y$ structure, and these were tested by Shrout and Bolger's method (see Appendix E). We analyzed hypothesized mediated paths, as well as significant direct impacts from controls on each dependent variable with a separate structural model.[24] Table 5 summarizes model fit statistics for all three final models. Each model had an acceptable fit. The base innovation model ($\chi(6) = 96.72$, $p = .008$) had an acceptable PClose of .22, and all the regression weights for all paths are significant. The RMSEA is .06 with a narrow range between the lower and upper bound of a 90 percent confidence interval (.03, .09). The values for CFI (.94), PCFI (.68) and SRMR (.06) are also acceptable (Arbuckle and Wothke 1999). As indicated, the process and service innovation models had equally good fit indices. The covariance matrix used SEM analyses and is found in Appendix F.

Findings

Test results are summarized in Tables 6, 7, and 8. The significant paths including the types of mediation involved, their significance, coefficient betas, and R^2s are illustrated in Figures 4, 5, and 6.

What Affects the Level of Radical Base Innovation?

As shown in Figure 4, our final model explains 24 percent of the variation in base innovation. At the same time, the model explains 37 percent of the variance in sensing and 47 percent of the variance experimentation, thus confirming the ACAP's mediated structure. The level of radical base innovation is also positively influenced by customer pressure (Std. Est. = .16, $p = .06$).

[23]Prior studies rarely measure the level of radicalness. Srinivasan et al. (2002) define radical "e-Business" to range from uses of e-mail to developing new business models, which misses architectural discontinuity in radical innovation and conflates measures of *radical* innovation and the *type* of IT innovation. Koberg et al. (2003, p. 35) define radical innovation as the "creation of new major products/service programs leading to expansion of current markets." This conflates incremental and radical innovation.

[24]The mediated impact of each knowledge factor on each innovation outcome was tested separately. An integrated model was also run, where all three models were combined. The coefficients for all paths and the variances explained for all dependent variables remained virtually the same, increasing confidence for the findings. The mediation paths in the integrated model are, however, too complex for mediation analysis, as no available statistical package can estimate the total *and* specific indirect effects when a model has more than one mediated path where *each* mediation path has more than one mediator. In addition, since our theory states that all knowledge factors are antecedents for all innovation types, introducing all the innovation types into the integrated model is likely to lead to spurious results due to multicollinearity (Preacher and Hayes 2008).

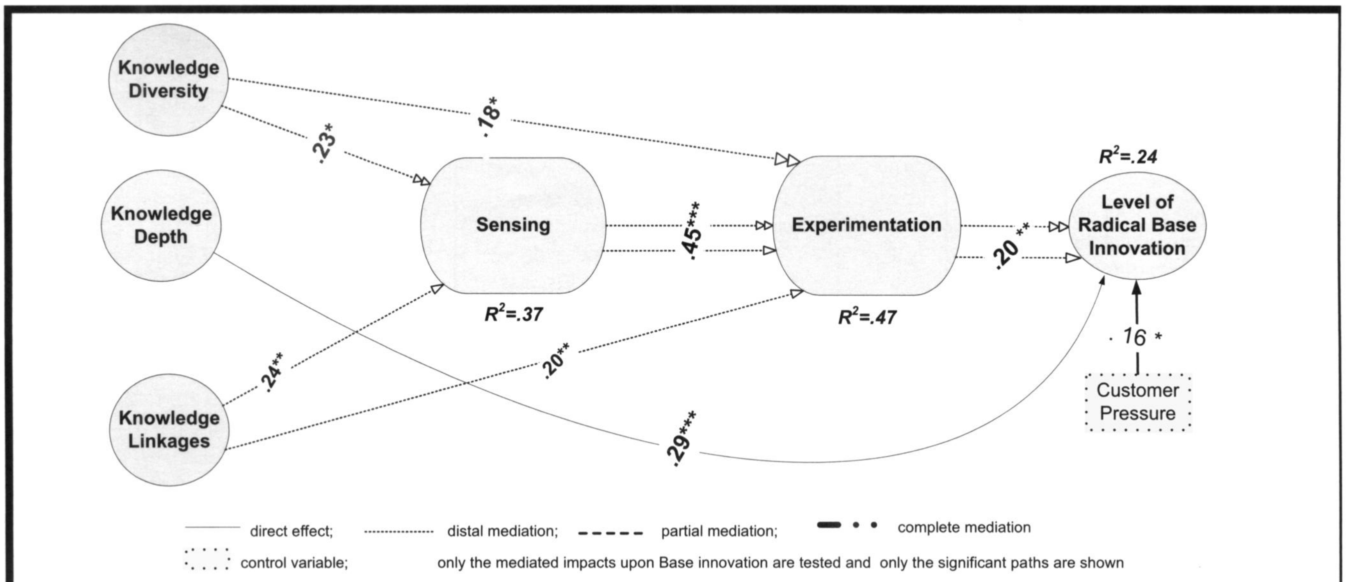
Table 5. Model Fit and Model Comparsions

Std. Path Parameter	X^2	df	RMSEA				CFI	PCFI	SRMR
				low	uppr	p			
Desired Level			< .08	Range	< .12	> .05	> .95	> .70	< .05
Base Innovation									
Complete mediation model	138.81	78	0.08	0.06	0.10	0.00	0.88	0.66	0.07
Direct effect model	17.93	8	0.10	0.04	0.17	0.08	0.96	0.36	0.04
Final model	96.72	66	0.06	0.03	0.09	0.22	0.94	0.68	0.06
Process Innovation									
Complete mediation model	154.34	94	0.07	0.05	0.09	0.04	0.90	0.63	0.07
Direct effect model	N/A: No latent variables								
Final model	98.06	57	0.08	0.05	0.10	0.05	0.93	0.58	0.07
Service Innovation									
Complete mediation model	140.18	84	0.08	0.05	0.10	0.04	0.90	0.63	0.07
Direct effect model	18.39	10	0.08	0.01	0.14	0.16	0.97	0.35	0.04
Final model	66.56	45	0.06	0.03	0.09	0.24	0.95	0.65	0.06

Table 6. Testing Indirect Effects of Knowledge Factors on Radical Base Innovation

H	Mediation Path		Path	Bootstrap		Bias Corrected	
				Unstd. Est.	SE	90% CI	Sig.
HB1	Knowledge diversity → Sensing → Experimentation → Base **(distal mediation)**	a	Knowledge diversity → Sensing	0.13	0.09	(0.01, 0.32)	**0.07**
		b	Sensing → Experimentation	0.60	0.28	(0.24, 1.13)	**0.02**
		c	Experimentation → Base	0.25	0.28	(-0.17, 0.67)	0.32
		e	Knowledge diversity → Experimentation	0.18	0.09	(0.04, 0.32)	**0.03**
		f	Sensing → Base	0.14	0.41	(-0.45, 0.69)	0.67
		c'	Knowledge diversity → Base	0.04	0.14	(-0.20, 0.28)	0.81
		abc+af+ec	Knowledge diversity → Base	0.08	0.06	(-0.00, 0.21)	**0.10**
		C	Knowledge diversity → base	0.13	0.14	(-0.09, 0.36)	0.37
HB2	Knowledge depth → Sensing → Experimentation → Base **(direct effect)**	a	Knowledge depth → Sensing	0.20	0.09	(0.05, 0.35)	**0.30**
		b	Sensing → Experimentation	0.60	0.28	(0.24, 1.13)	**0.02**
		c	Experimentation → Base	0.25	0.28	(-0.17, 0.67)	0.32
		e	Knowledge depth → Experimentation	-0.11	0.09	(-0.26, 0.04)	0.24
		f	Sensing → Base	0.14	0.41	(-0.45, 0.69)	0.67
		c'	Knowledge depth → Base	0.27	0.14	(0.05, 0.50)	**0.05**
		abc+af+ec	Knowledge depth → Base	0.03	0.09	(-0.08, 0.17)	0.57
		C	Knowledge depth → Base	0.30	0.12	(0.12, 0.31)	**0.01**
HB3	Knowledge linkages → Sensing → Experimentation → Base **(distal mediation)**	a	Knowledge linkages → Sensing	0.14	0.07	(0.04, 0.29)	**0.02**
		b	Sensing → Experimentation	0.60	0.28	(0.24, 1.13)	**0.02**
		c	Experimentation → Base	0.25	0.28	(-0.17, 0.67)	0.32
		e	Knowledge linkages → Experimentation	0.16	0.09	(0.02, 0.31)	**0.08**
		f	Sensing → Base	0.14	0.41	(-0.45, 0.69)	0.67
		c'	Knowledge linkages → Base	-0.09	0.11	(-0.28, 0.07)	0.33
		abc+af+ec	Knowledge linkages → Base	0.08	0.06	(0.02, 0.21)	**0.07**
		C	Knowledge linkages → Base	-0.01	0.09	(-0.17, 0.13)	0.09

Note: a, b, e, f, c': Direct effect; a*b: Indirect effect; C: Total effect.



***$p \leq 0.01$; **$p \leq 0.05$; *$p \leq 0.1$

Note: The continuous mediated effect is reflected by both the *direction* and the *shape* of the arrow. Knowledge Diversity and Knowledge Linkages each distally influence Base through Sensing and Experimentation; Knowledge Diversity and Knowledge Linkages each also distally influence Base through Experimentation only; while Knowledge Depth only directly influences Base. (Double-headed dashed arrow: mediate impact of Knowledge Diversity; single-headed dashed arrow: mediated impact of Knowledge Linkages.)

Figure 4. Knowledge Factors and Their Influence on Base Innovation (Standardized Estimates)

Of the three hypothesized external paths (HB1-3) influencing ***base innovation***, we found support for two mediation effects (Table 6). ***Knowledge diversity*** and ***knowledge linkages*** do not directly impact base innovation as the total effect C for both paths are nonsignificant (Unstd. Est. = .13 at p = .37; Unstd. Est. = -.01 at p = .90 respectively). As hypothesized, they *distally* impact base innovation through *both* sensing and experimentation: the indirect effect path (abc+af+ec) is significant for knowledge diversity (**supporting HB1;** Unstd. Est. = .08; p = .10), and for knowledge linkages, (**supporting HB3**; Unstd. Est. = .08; p = .07). Surprisingly, the level of base innovation is directly influenced by ***knowledge depth*** (path C: Unstd. Est. = .30, p = .01), rejecting **HB2,** but indicating a significant, positive, direct impact of knowledge depth on base innovation.

As indicated in Table 6, the direct effect of knowledge diversity on experimentation is significant (Unstd. Est. = .18 at p = .03) suggesting that sensing *partially mediates* the effect of knowledge diversity on experimentation. Thus, the effect of knowledge diversity can sometimes bypass sensing, and affect experimentation directly during external base-innovation adoption. Likewise, a direct effect of knowledge linkages on experimentation is significant (Unstd. Est. = .16 at p = .08) indicating sensing partially mediates the effect of knowledge linkages on experimentation. Nevertheless, in both cases, experimentation forms an obligatory mediator in the external path that finally transmits the impact of knowledge linkages and knowledge diversity on base innovation as hypothesized.

What Affects the Level of Radical Process Innovation?

Figure 5 demonstrates that an SSF's propensity to engage in process innovation is positively influenced by the number of base innovations (Std. Est. = .47, p = 0) and service innovations it has adopted (Std. Est. = .24, p = 0), as well as its size (Std. Est. = .16, p = .01). The model explains 58 percent of the variance in process innovation.

Among the three hypothesized external paths influencing ***process innovation,*** one mediation effect was found (Table 7): the impact of ***knowledge linkages*** upon process innovation is *completely* mediated through sensing and experimentation **supporting** the **full mediation** hypothesis for **HP3**. First, knowledge linkages directly affect an SSF's pro-

Table 7. Testing Indirect Effects of Knowledge Factors on Radical Process Innovation

H	Mediation Path		Path	Bootstrap Unstd. Est.	Bootstrap SE	Bias Corrected 90% CI	Bias Corrected Sig.
HP1	Knowledge diversity → Sensing → Experimentation → Process **(direct)**	a	Knowledge diversity → Sensing	0.14	0.09	(0.01, 0.32)	**0.07**
		b	Sensing → Experimentation	0.59	0.28	(0.22, 1.12)	**0.02**
		c	Experimentation → Process	0.29	0.22	(0.04, 0.31)	**0.08**
		e	Knowledge diversity → Experimentation	0.18	0.08	(0.00, 0.31)	**0.04**
		f	Sensing → Process	-0.10	0.28	(-0.64, 0.26)	0.28
		c'	Knowledge diversity → Process	0.16	0.09	(0.00, 0.31)	**0.10**
		abc+af+ec	Knowledge diversity → Process	0.06	0.06	(-0.01, 0.17)	0.16
		C	Knowledge diversity → Process	0.22	0.09	(0.05, 0.35)	**0.03**
HP2	Knowledge depth → Sensing → Experimentation → Process **(direct)**	a	Knowledge depth → Sensing	0.20	0.09	(0.05, 0.35)	**0.03**
		b	Sensing → Experimentation	0.59	0.28	(0.22, 1.12)	**0.02**
		c	Experimentation → Process	0.29	0.22	(0.04, 0.31)	**0.08**
		e	Knowledge depth → Experimentation	-0.10	0.09	(-0.26, 0.04)	0.25
		f	Sensing → Process	-0.10	0.28	(-0.64, 0.26)	0.28
		c'	Knowledge depth → Process	-0.19	0.09	(-0.34, -0.04)	**0.05**
		abc+af+ec	Knowledge depth → Process	-0.02	0.06	(-0.13, 0.06)	0.63
		C	Knowledge depth → Process	-0.21	0.07	(-0.32, -0.10)	**0.01**
HP3	Knowledge linkages → Sensing → Experimentation → Process **(complete)**	a	Knowledge linkages → Sensing	0.15	0.08	(0.04, 0.30)	**0.02**
		b	Sensing → Experimentation	0.59	0.28	(0.22, 1.12)	**0.02**
		c	Experimentation → Process	0.29	0.22	(0.04, 0.31)	**0.08**
		e	Knowledge linkages → Experimentation	0.16	0.09	(0.02, 0.31)	**0.07**
		f	Sensing → Process	-0.10	0.28	(-0.64, 0.26)	0.28
		c'	Knowledge linkages → Process	0.07	0.09	(-0.07, 0.22)	0.38
		abc+af+ec	Knowledge linkages → Process	0.06	0.05	(0.00, 0.16)	**0.10**
		C	Knowledge linkages → Process	0.12	0.07	(0.01, 0.25)	**0.08**
HP4	Knowledge diversity → Experimentation → Process **(direct)**	a	Knowledge diversity → Experimentation	0.18	0.08	(0.00, 0.31)	**0.04**
		b	Experimentation → Process	0.29	0.22	(0.04, 0.31)	**0.04**
		c'	Knowledge diversity → Process	0.16	0.09	(0.00, 0.31)	**0.10**
		abc+af+ec	Knowledge diversity → Process	0.06	0.06	(-0.01, 0.17)	0.16
		C	Knowledge diversity → Process	0.22	0.09	(0.05, 0.35)	**0.03**
HB5	Knowledge depth → Experimentation → Process **(direct)**	a	Knowledge depth → Experimentation	-0.10	0.09	(-0.26, 0.04)	0.25
		b	Experimentation → Process	0.29	0.22	(0.04, 0.31)	**0.08**
		c'	Experimentation → Process	-0.19	0.09	(-0.34, -0.04)	**0.05**
		abc+af+ec	Experimentation → Process	-0.02	0.06	(-0.13, 0.06)	0.63
		C	Experimentation → Process	-0.21	0.07	(-0.32, -0.10)	**0.01**

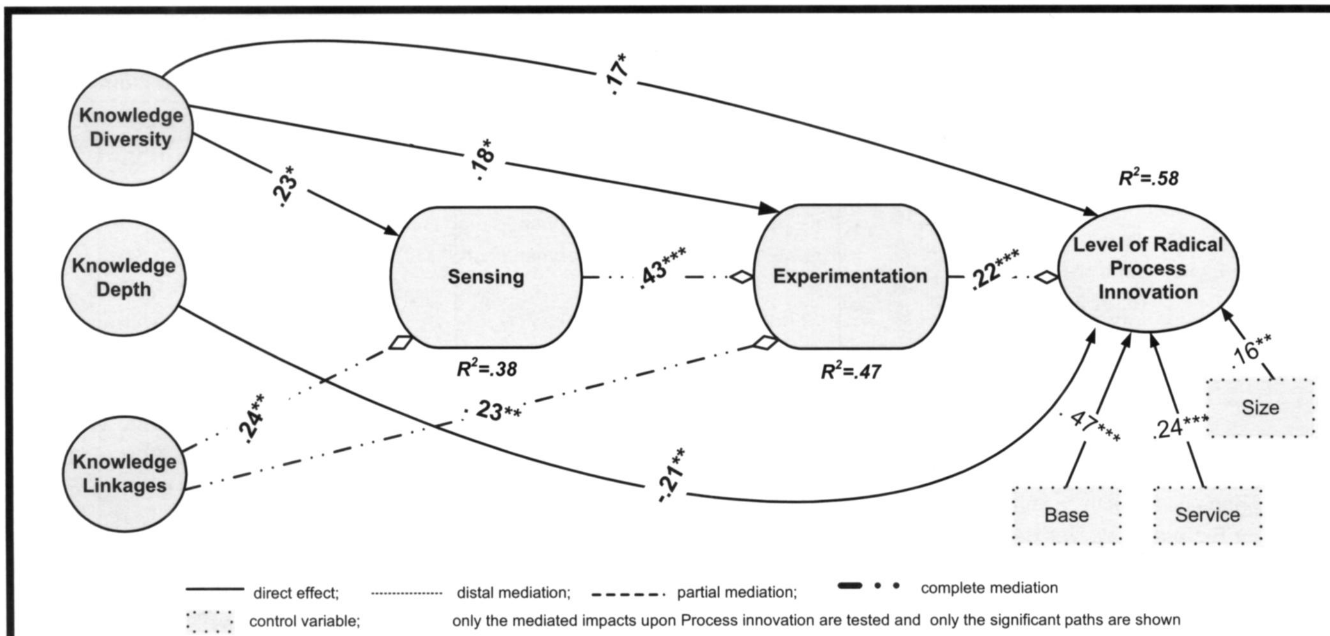
Note: a, b, e, f, c': Direct effect; a*b: Indirect effect; C: Total effect.

pensity to adopt process innovations (Unstd. Est. = .12, p = .08) (path C). After sensing and experimentation enter into the model, the direct effect is no longer significant (Unstd. Est. = .07, p = .38) (path c') while the indirect effect (abc+af+ec) is significant (Unstd. Est. = .06, p = .10). These results demonstrate full mediation. As shown in Table 6, the direct effect from knowledge linkage to experimentation is also significant (Unstd. Est. = .16 at p = .07). This is a combination of two effects: (1) the partial mediation of the impact of knowledge linkages on experimentation by sensing (due to the presence of the external path); and (2) and the influence of knowledge linkages on process innovation through experimentation. Nevertheless, here experimentation forms an obligatory, full mediator for transmitting the impact of knowledge linkages upon process innovation.

No significant mediation effects in external or internal paths were detected for either ***knowledge diversity*** or ***knowledge depth.*** Instead, surprisingly, an SSF's propensity to innovate with process innovations was *directly* and *positively influenced* by ***knowledge diversity*** (path C: Unstd. Est. =.22, p = .03) (**rejecting HP1** and **HP4**), while *negatively* and *directly influenced* by ***knowledge depth*** (path C: Unstd. Est. =-.21, p = .01) (**rejecting HP2** and **HP5**).

What Affects the Level of Radical Service Innovation?

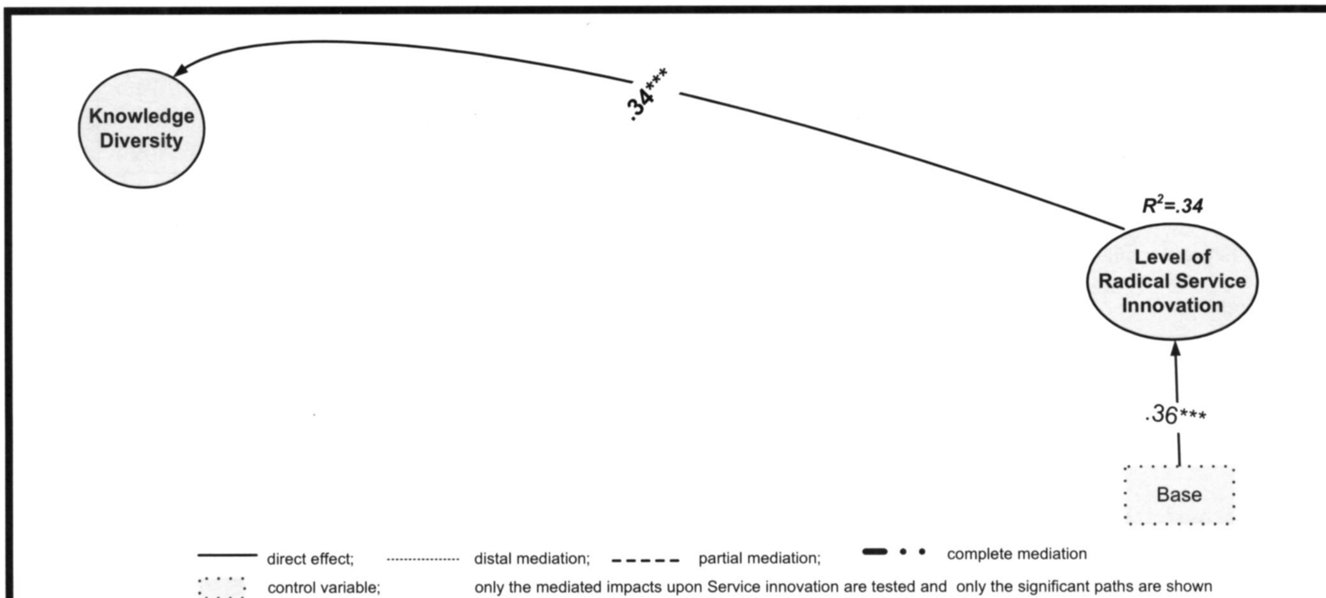
An SSF's propensity to innovate with services is positively influenced by its level of base innovation (Std. Est. = .36, p



***p ≤ 0.01; **p ≤ 0.05; *p ≤ 0.1

Note: The continuous mediated effect is reflected by both the *direction* and the *shape* of the arrow. Knowledge Linkages' impact upon Process is completely mediated through Sensing and Experimentation; Knowledge Linkages also distally influence Process through Experimentation only; while Knowledge Depth and Knowledge Diversity each only directly influences Process. (Diamond-headed dashed arrow: mediated impact of Knowledge Linkages.)

Figure 5. Knowledge Factors and Their Influence on Process Innovation (Standardized Estimates)



***p ≤ 0.01; **p ≤ 0.05; *p ≤ 0.1

Note: Only Knowledge Diversity among all of the knowledge factors directly influences Service.

Figure 6. Knowledge Factors and Their Influence on Service Innovation (Standardized Estimates)

Table 8. Testing Indirect Effects of Knowledge Factors on Radical Service Innovation

				Bootstrap		Bias Corrected	
H	**Mediation Path**		**Path**	**Unstd. Est.**	**SE**	**90% CI**	**Sig.**
HS1	Knowledge diversity → Sensing → Experimentation → Service **(direct)**	a	Knowledge diversity → Sensing	0.14	0.09	(0.02, 0.33)	**0.07**
		b	Sensing → Experimentation	0.58	0.28	(0.22, 1.08)	**0.02**
		c	Experimentation → Service	n.a.	n.a.	n.a.	n.a.
		e	Knowledge diversity → Experimentation	0.18	0.09	(0.04, 0.31)	**0.04**
		f	Sensing → Service	0.17	0.22	(-0.25, 0.47)	0.48
		c'	Knowledge diversity → Service	0.28	0.12	(0.10, 0.48)	**0.01**
		abc+af+ec	Knowledge diversity → Service	0.02	0.04	(-0.01, 0.12)	0.26
		C	Knowledge diversity → Service	0.30	0.12	(0.11, 0.50)	**0.01**
HS2	Knowledge depth → Sensing → Experimentation → Service **(none)**	a	Knowledge depth → Sensing	0.20	0.09	(0.05, 0.35)	**0.03**
		b	Sensing → Experimentation	0.58	0.28	(0.22, 1.08)	**0.02**
		c	Experimentation → Service	n.a.	n.a.	n.a.	n.a.
		e	Knowledge depth → Experimentation	-0.10	0.09	(-0.26, 0.04)	0.25
		f	Sensing → Service	0.17	0.22	(-0.25, 0.47)	0.48
		c'	Knowledge depth → Service	0.02	0.12	(-0.06, 0.22)	0.90
		abc+af+ec	Knowledge depth → Service	0.03	0.04	(-0.02, 0.11)	0.30
		C	Knowledge depth → Service	0.06	0.11	(-0.12, 0.23)	0.65
HS3	Knowledge linkages → Sensing → Experimentation → Service **(none)**	a	Knowledge linkages → Sensing	0.15	0.08	(0.04, 0.31)	**0.02**
		b	Sensing → Experimentation	0.58	0.28	(0.22, 1.08)	**0.02**
		c	Experimentation → Service	n.a.	n.a.	n.a.	n.a.
		e	Knowledge linkages → Experimentation	0.16	0.09	(0.02, 0.31)	**0.08**
		f	Sensing → Service	0.17	0.22	(-0.25, 0.47)	0.48
		c'	Knowledge diversity → Service	-0.09	0.10	(-0.25, 0.10)	0.45
		abc+af+ec	Knowledge diversity → Service	0.03	0.04	(-0.01, 0.11)	0.31
		C	Knowledge diversity → Service	-0.06	0.10	(-0.21, 0.10)	0.56
HS4	Knowledge diversity → Experimentation → Service **(direct)**	a	Knowledge diversity → Experimentation	0.18	0.09	(0.04, 0.31)	**0.04**
		b	Experimentation → Service	n.a.	n.a.	n.a.	n.a.
		c'	Knowledge diversity → Service	0.28	0.12	(0.10, 0.48)	**0.01**
		abc+af+ec	Knowledge diversity → Service	0.02	0.04	(-0.01, 0.12)	0.25
		C	Knowledge diversity → Service	0.30	0.12	(0.11, 0.50)	**0.01**
HS5	Knowledge depth → Experimentation → Service **(none)**	a	Sensing → Experimentation	0.58	0.28	(0.22, 1.08)	**0.02**
		b	Experimentation → Service	n.a.	n.a.	n.a.	n.a.
		c'	Knowledge depth → Service	0.02	0.12	(-0.16, 0.22)	0.09
		abc+af+ec	Knowledge depth → Service	0.03	0.04	(-0.02, 011)	0.30
		C	Knowledge depth → Service	0.06	0.11	(-0.12, 0.23)	0.65

Note: a, b, e, f, c': Direct effect; a*b: Indirect effect; C: Total effect.

= 0). The model explains 34 percent of the variance in service innovation (Figure 6). None of the three hypothesized external paths influencing ***service innovation*** were significant **rejecting HS1, HS2,** and **HS3** (Table 8). Likewise, neither knowledge diversity nor knowledge depth influenced service innovation through internal paths, **rejecting HS4** and **HS5**. In contrast, ***knowledge diversity*** *directly* and *positively* influences service innovation (Unstd. Est. = .30; p = .01).

Model Fit and Alternative Model Tests

Following Mathieu and Taylor (2006), two other sets of models were run to exclude rival explanations: one specified direct effects from all knowledge factors to the level of innovation (without mediation); the other specified routines that completely mediate all of the relationships between the knowledge base and innovation outcomes (Table 5). The results yielded a larger amount of insignificant path estimates for the hypothesized paths. As shown in Table 5, the alternative models have worse Chi square, PClose, PCFI, SRMR and RMSEA values.

Discussion and Conclusions

Summary

A complete list of the hypotheses and the test results are provided in Table 9. In light of these results, the next section reviews how well the four initial research questions were addressed: (1) What is an encompassing set of knowledge factors affecting radical IT innovation? (2) How can these knowledge factors be organized into a knowledge-based model explaining radical IT innovation? (3) What influence does each knowledge factor, separately and in combination, have on different types of radical IT innovation? (4) What is the role of innovation ecologies in this processes? In addressing the first question, the ACAP lens was adopted to unify strands of innovation research by integrating five knowledge factors. While not necessarily complete, this is one of the first studies to examine such a comprehensive list of factors and their effect on radical IT innovation, thus presenting a more complete interpretation of ACAP and its effects.

To address the second question, the ACAP lens organized knowledge factors into a mediated model. Strong support for the mediated nature of ACAP in explaining the level of external base innovation was found (Table 10).[25] As hypothesized, both knowledge diversity and knowledge linkages impacted base innovation through the mediated external path. Evidence for partial mediation of sensing on experimentation was also found, as both knowledge diversity and knowledge linkages also directly influenced experimentation within this external path. Thus, firms with diverse knowledge and broad knowledge networks are more likely to experiment, and resultantly engage in higher levels of base innovation. Within base innovations, however, in contrast to expectations, two separate knowledge-related mechanisms were detected: one *mediated* externally and driven by knowledge diversity and linkages, where a firm's ACAP "pulled" external knowledge through sensing and experimentation to adopt more base innovations; and one *direct* effect, driven by knowledge depth, where technical experts "pushed" technical advances within their domains. With all knowledge factors affecting *base innovation,* however, our findings suggest that base innovation demands intense firm-level knowledge coordination.

Contrary to predictions, little support was found for explaining process innovation with the mediated ACAP model, and no support was found in explaining service innovation. In contrast, process innovations are influenced (1) in a fully mediated manner by knowledge linkages through sensing and experimentation, (2) directly and positively by knowledge diversity, and (3) directly and negatively by knowledge depth. The last, surprising, finding appears to result from a competency trap: Experts seek to avoid radical process changes when they possess highly invested technological knowledge. This makes them at uneasy about relinquishing highly invested knowledge even when it is demanded by new base and service innovations. Accordingly, with process innovations we note the presence of two distinct knowledge based mechanisms: (1) one external and ACAP based (driven by knowledge linkages), which "pulls" external knowledge through sensing and experimentation; and (2) one direct (driven by knowledge depth and diversity), where deeper technical expertise impedes radical process changes, while increased knowledge diversity in combination with base and service innovation knowledge promote radical process change. Yet, none of the knowledge base factors influence the level of sensing *or* experimentation prior to directly affecting the level of service innovation. In contrast, *direct* effects of knowledge diversity with service innovation were observed.

While addressing the third question, varying influences of specific combinations of knowledge factors across three IT innovation types were detected. This finding is consistent with prior studies (Table 10) (Grover et al. 1997; Lyytinen and Rose 2003a, 2003b; Pries-Heje et al. 2004; Swanson 1994). The most unexpected finding was the presence of highly distinct combinations of knowledge antecedents for each IT innovation type, which influenced the overall "flow" of radical IT innovation within SF's innovation ecology. To wit, each knowledge factor exercised quite unique effects in how the heterogeneous knowledge circulated within the ecology, reflecting a form of an innovation "cascade": (1) knowledge base factors influenced routine factors to "draw in" or push base innovations; (2) once the base innovation related knowledge was assimilated and tried out, routine factors ceased to play a dominant role, and (3) order effects and related knowledge impacts (emanating from the adopted knowledge that came with base and service innovations) kicked in, and overwhelmed most mediating effects of the routines. By including them as control variables in our model, we anticipated these order effects to *complement* the

[25]This includes also the paths Sensing → Experiment → Base/Process Innovation. These paths were not hypothesized per se, but were part of the mediated paths, which were found to be significant.

Table 9. Research Hypotheses and Results

H	Mediation Path	Hypothesis	Supported?
HB1	Knowledge Diversity → Sensing → Experimentation → Base	Knowledge diversity positively influences the level of Sensing and Experimentation, which influences positively the level of Base Innovation, Knowledge Diversity will not directly influence Base Innovation.	Yes
HB2	Knowledge Depth → Sensing → Experimentation → Base	Knowledge Depth influences positively the level of Sensing and Experimentation, which influences positively the level of Base Innovation. Knowledge Depth will not directly influence Base Innovation.	No (Knowledge Depth directly influences Base Innovation)
HB3	Knowledge Linkages → Sensing → Experimentation → Process	Knowledge Linkages positively influence the level of Sensing and Experimentation, which influences positively the level of Base Innovation. Knowledge Linkages will not directly influence Process Innovation.	Yes
HP1	Knowlege Diversity → Sensing → Experimentation → Process	Knowledge Diversity influences positively the level of Sensing and Experimentation, which influences positively the level of Process Innovation. Knowledge Diversity will not directly influence Process Innovation.	No (Knowledge Diversity directly influences Process Innovation)
HP2	Knowledge Depth → Sensing → Experimentation → Process	Knowledge Depth positively influences the level of Sensing and Experimentation, which influences positively the level of Process Innovation. Knowledge Depth will not directly influence Process Innovation.	No (Knowledge Depth directly influences Process Innovation)
HP3	Knowledge Linkages → Sensing → Experimentation → Process	Knowledge Linkages positively influence the level of Sensing and Experimentation, which influences positively the level of Process Innovation. Knowledge Linkages will not directly influence Process Innovation.	Yes
HP4	Knowledge Diversity → Experimentation → Process	Knowledge Diversity influences positively the level of Experimentation, which influences positively the level of Process Innovation. Knowledge Diversity will not directly influence Process Innovation.	No (Knowledge Diversity directly influences Process Innovation)
HP5	Knowledge Depth → Experimentation → Process	Knowledge Depth influences positively the level of Experimentation, which influences positively the level of Process Innovation. Knowledge Depth will not directly influence Process Innovation.	No (Knowledge Depth directly influences Process Innovation)
HS1	Knowledge Diversity → Sensing → Experimentation → Service	Knowledge Diversity influences positively the level of Sensing and Experimentation, which influences positively the level of Service Innovation. Knowledge Diversity will not directly influence Service Innovation.	No (Knowledge Diversity directly influences Service Innovation)
HS2	Knowledge Depth → Sensing → Experimentation → Service	Knowledge Depth influences positively the level of Sensing and Experimentation, which influences positively the level of Service Innovation. Knowledge Depth will not directly influence Service Innovation.	No
HS3	Knowledge Linkages → Sensing → Experimentation → Service	Knowledge Linkages positively influence the level of Sensing and Experimentation, which influences positively the level of Service Innovation. Knowledge Linkages will not directly influence Service Innovation.	No
HS4	Knowledge Diversity → Experimentation → Service	Knowledge Diversity influences positively the level of Experimentation, which influences positively the level of Service Innovation. Knowledge Diversity will not directly influence Service Innovation.	No (Knowledge Diversity directly influences Service Innovation)
HS5	Knowledge Depth → Experimentation → Service	Knowledge Depth influences positively the level of Experimentation, which influences positively the level of Service Innovation. Knowledge Depth will not directly influence Service Innovation.	No

Table 10. Summary of Innovation Predictors for Radical IT Innovation Types

Predictors \ Outcome Variables	Level of Radical Base Innovations	Level of Radical Process Innovations	Level of Radical Service Innovation
Knowledge Diversity	Distal mediation (+) **External Path**: *via Sensing → Experimentation*	Direct effect (+)	Direct effect (+)
Knowledge Depth	Direct effect (+)	Direct effect (–)	—
Knowledge Linkages	Distal mediation (+) **External Path**: *via Sensing → Experimentation*	Complete mediation (+) **External Path**: *via Sensing → Experimentation*	—
Sensing	Distal mediation (+) (*via Experimentation*)	Complete mediation (+) (*via Experimentation*)	—
Experimentation	Direct effect(+)	Direct effect (+)	—
Control Variables	*Customer Pressure* (+)	*Base* (+) *Service* (+) *Size* (+)	*Base* (+)

mediating effects of ACAP during process and service innovation. Instead, the effects of routine factors decreased to insignificant levels and were substituted by the effects of prior IT innovation-related learning, while the effects of single knowledge base factors became contextual and sporadic.

When the role of each knowledge base factor in shaping the radical IT innovation cascade is analyzed, knowledge depth has no impact on any routine factor regardless of the IT innovation type. Its effects were always direct. This bifurcating impact reflects the specific role of knowledge depth in shaping IT innovation, on one hand it pushes forward specific base innovations, while on the other hand it impedes process change. Likewise, only knowledge diversity positively affects each stage of the observed innovation cascade. It operates through routine factors during base innovation, but thereafter affects process and service innovation directly. Finally, as expected, knowledge linkages operated only through mediated ACAP whenever external knowledge is demanded (either during base or process innovation).

To address the fourth question, SFs are generally seen to engage in three types of IT innovation forming an ecology where (1) prior innovations affect the levels of subsequent IT innovation and (2) different IT innovation types are affected by different combinations of prior IT innovations (Table 10). This interpretation moves research on radical IT innovation beyond focusing on singular IT innovation that has dominated innovation research and examine *transformative effects* of such innovations (Fichman and Kemerer 1997; Srinivasan et al. 2002; Subramanian and Nilakanta 1996).

Discussion

This paper contributes to research on both absorptive capacity and radical IT innovation. It advances the empirical validation of *absorptive capacity* on several fronts: ACAP measures, ACAP structure, relationships between ACAP and radical innovation, relationships between ACAP and combinative capabilities, and relationships between ACAP and IT.[26] With regard to *ACAP measures,* Zahra and George (2002), Lane et al. (2006), and Roberts et al. (2011) were followed and ACAP was approached as a capability. Here the contributions are twofold. First, prior analyses of firm knowledge dimensions were integrated (Cohen and Levinthal 1990; Lane et al. 2006; Mowery and Oxley 1995; Tsai 2001) into three constructs: diversity, depth, and linkages. This is highly consistent with the nature of knowledge residing within SFs, and overcomes limitations of prior measures such as patents (Ahuja and Katila 2001; Cohen and Levinthal 1990). Combining with direct measures of innovations, these ACAP constructs also alleviated threats to their internal and external validity (Lane et al. 2006).

[26]Other research has been concerned with impacts of ACAP on intra-organizational knowledge transfer and inter-organizational learning (Gupta and Govindarajan 2000; Szulanski 1996), knowledge-based organizational change (Lewin and Volberda 1999; Van Den Bosch et al. 1999), firm performance (Lane et al. 2001), and organizational antecedents (Jansen et al. 2005). For an excellent review of the ACAP construct in IS research, see Roberts et al. (2011). Overall different results about ACAP need to be approached with caution as definitions and measures vary significantly and typically *do not* assess the impact of the same set of factors.

The critical role of routines in creating ACAP as a structural capability is also recognized by this study. The routines are composed of *both* sensing and experimentation, where each distinct set involves distinct knowledge processes as captured by the detected effects: knowledge base → sensing, sensing → experimenting, experimenting → innovation, etc. By integrating all of these processes into a unified, interrelated model, this study is one of the first to systematically examine the impact of several interrelated ACAP elements on innovation as recently requested by Lane et al. (2006) and Roberts et al. (2011). While earlier research (Cohen and Levinthal 1990; Lane et al. 2006; Zahra and George 2002) rightly emphasizes that ACAP elements enter into systemic interrelationships, this study is the first to explicate ACAP as a dynamic capability with interrelated elements. Indeed, the knowledge base factors are shown to be mobilized in unique ways, ultimately leading to increased innovation across different IT innovation types.[27] Strong support for a mediated ACAP model was also found for the first time, as nearly all of its hypothesized external paths were corroborated when the furnished knowledge was extramural (Figure 4). This observation invites future investigations that can better distinguish separate effects of internal knowledge, external knowledge absorption, and experimental routines during innovation.

The study addresses the paucity of research on *ACAP's role in radical innovation*. It confirms ACAP's positive impact on the firm-level innovativeness (Ahuja and Katila 2001; Fosfuri and Tribó 2008; Liao et al. 2007; Tsai 2001). It also confirms Lane et al.'s (2006, p. 850) claim that during radical innovation, "absorptive capacity is based on a broad range of loosely related knowledge domains." Indeed, we found that knowledge diversity affected all types of radical IT innovation. Earlier research has scantily examined how *combinative capabilities* (system capabilities, coordination capabilities, and socialization capabilities) affect the firm's ability to identify, integrate, and apply knowledge for innovation (Cohen and Levinthal 1990; Jansen et al. 2005; Van Den Bosch et al. 1999). In this regard, this study focuses on the role of system capabilities and identifies multiple ways in which heterogeneous knowledge factors influence the combinative process of knowledge integration, and how its different paths of influence depend on the type of IT innovation. Finally, the study is one of the first to examine how *ACAP affects IT innovation,* a significant research challenge identified by Roberts et al. (2011).

The study advances *radical IT innovation research* on several fronts. Fichman (2004) notes that the mainstream IT innovation research, by focusing on explaining the diffusion of a singular innovation, "has reached the point of diminishing returns as a framework for supporting ground breaking research" (p. 314). We agree, and this study deviates in many ways from the dominant paradigm. First, it extensively theorizes on a firms' knowledge-related capabilities (Fichman and Kemerer 1997, Grover et al. 2007) that help firms overcome innovation novelty. Unlike prior diffusion research emphasizing the "easy-to-use" features of IT innovations, this study focuses on innovations that are difficult-to-observe and ambiguous. This study also responds to Fichman's (2004) call to analyze innovation configurations by understanding how varying configurations of knowledge factors affect the level of specific IT innovation types.

Fichman (2004) also notes that past research has largely ignored the "quality" of innovation (i.e., the extent to which a firm has adopted the right innovation, at the right time, and in the right way). Again, this study provides two contributions. First, it advances IT innovation research by looking at complex IT innovation dynamics influenced by a firm's epistemic and behavioral knowledge factors as well as "order effects" emanating from its prior innovations (Carlo et al. 2011). Most likely, different effects would have been observed had the interactions between IT innovations been weak and their level of novelty low. In such contexts, the current "one innovation at a time" approach would have been more appropriate. Finally, the study reveals that in some innovation contexts, research needs to relinguish the idea that *either* IT innovations are adopted externally and diffuse, *or* they are internally created and assimilated. In contrast, both options coexist when SFs face disruptive technologies.

Practical Implications

This study offers several lessons for managers. First, innovating firms need to be mindful about developing their knowledge-based capabilities and investing in all elements of their absorptive capacity. They need to consider where, when, and how to expand their knowledge diversity, how they can manage external relationships, and how much and when they should invest in knowledge depth. For instance, increasing knowledge depth will promote a firm's propensity to engage in radical base innovations, but managers should be aware of its adverse effects if they want to engage in subsequent process innovations. Building strong relationships within the environment is beneficial for radical base and process innovation, but not instrumental for service innovation. Likewise, the influence of knowledge diversity on base innovation and linkages on base and process innovation takes place through external paths. Therefore, managers need to recognize the significant impacts of sensing (Lyytinen et al

[27] Some research (Eriksson and Chetty 2003; Minbaeva et al. 2003) has examined the mediating role of absorptive capacity, but only taps into its static dimension (e.g., prior experience, employee's ability).

2010) and experimentation (Minbaeva et al. 2003; Zahra and George 2002) by investing in social relationships, systems, search-related routines, and the like.

Limitations

We note five limitations. First, we focused on small SFs while the bulk of earlier research has studied larger firms (Fichman and Kemerer 1997; Germain 1996; Grover et al. 1997; Koberg et al. 2003). Because several factors such as structural complexity and slack are absent in small firms, and the effects of some knowledge factors (diversity, linkages) vary between small and large firms, we only cautiously generalize our findings. As a result, internal sources of base innovations may be critical in other types of SFs, and suggest different causal paths. Second, our study may suffer from the threat of *recall bias*. This limitation appears to be a necessary sacrifice of conducting research on radical innovation. Interviews with experts indicated that radicalness of innovation can only be assessed after the magnitude of its impact is observed after time has elapsed from initial adoption. Further, prior research (Dahlin and Behrens 2005) suggests that the threat of hindsight bias is less severe than foresight bias for radical innovation. The third limitation is the potential inaccuracy of recall in what innovations were adopted. Fortunately, Internet computing was so significant that the participants in our study, as admitted during the talk-aloud protocols, could easily recall past events. Fourth, the somewhat limited measures of absorptive capacity for its epistemic and behavioral dimensions may influence its internal validity. Several items had to be dropped, because they did not align with our theorized constructs. For instance, we used measures that failed to delineate between external and internal type of experimentation. Fifth, when operationalizing the innovation constructs, we had to walk a fine line between generalizability and domain specificity. In particular, the process innovation construct may not capture all innovative *ways* to envision, design, and implement software by SFs facing Internet computing. Some of the process innovations included in the measure may not be solely associated with Internet computing, even though every effort was made to assure that studied process innovations were adopted only after SFs had adopted Internet computing platforms.

Future Research

The findings suggest several avenues for future research. First, more research is needed to delineate the role of routines in how firms leverage their knowledge base. Since routines mediate in both distal and proximal ways, it is unclear how to account for these differentiated impacts. Second, it is possible that the knowledge factors included have interaction effects that were neither theorized nor tested. Third, sensing and experimenting are just two of the mechanisms that mediate the effects of the knowledge base. It is also worthwhile to study effects of other capabilities including coordination, or socialization. Likewise, IT innovation constructs will continue to evolve as new technical breakthroughs punctuate the IT landscape. Fourth, the knowledge base factors can be expanded to include other dimensions such as cross-functional interfaces. Fifth, how levels of innovation affect firm performance was not addressed. Clearly, just innovating more does not lead to higher levels of performance. Further research in selection and diffusion mechanisms is needed to better understand which knowledge-based mechanisms lead to superior firm performance. Sixth, the study could be extended by exploring the temporal impact of knowledge factors over time during the whole innovation cycle.[28] Seventh, the internal path for base innovations can be included when studying large SFs or advanced IT units with extensive technical expertise and resources.

Acknowledgments

The paper has benefited from the helpful comments of the senior editor, the associate editor, three anonymous reviewers, Michel Avital, Fred Collopy, Nick Berente, Sean Hansen, Danail Ivanov, Sean McGann, Jagdip Singh, David Tilson, Betty Vandenbosch, Youngjin Yoo, (Kevin) Jun Ye, David Gefen, Ron Thompson, and Wynne Chin. We thank also faculties at American University, Arizona State University, Houston University, University of Maryland, University of St. Louis, Iowa State University, The University of Western Ontario, National University (Taiwan), City University of Hong Kong, Victoria University (New Zealand), University of Amsterdam, and Case Western Reserve University for their comments. We want to thank all those who participated in the study for sharing their experience.

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[28]We thank an anonymous reviewer for shedding light on this.

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