Explaining Information Technology and Business Innovations: The Role of Cumulative Experience and Performance Feedback

Completed Research Paper

Introduction

Research on organizational IT innovations has generated a substantial body of insights. In this paper we draw particular attention to the thesis that IT implementations build crucial capabilities which are then typically redeployed for future IT innovations. Indeed, it is commonly accepted that organizational innovations do not take place in a historical vacuum but instead, the history of prior innovations shapes future innovations. Deliberate organizational learning is obvious in most research of how organizations document their learning from IT projects for the purpose of applying it in the future. Alternately, referred to as information technology (IT) projects (Keil 1995; Mitchell and Zmud 1999; Moore 1979), or IT implementations (Markus et al. 2000; Swanson 1994), IT innovations hone IT capabilities through experiential learning (Chan and Reich 2007; Garud and Kumaraswamy 2005; Leonard-Barton 1988; Mitchell 2006; Newell et al. 2006; Robey et al. 2002; Whitaker et al. 2010) or vicariously, through interaction with IT vendors and consultants (Ko et al. 2005; Levina and Ross 2003; Swanson and Ramiller 1997; Swanson and Ramiller 2004), and thus enable organizations to rapidly assess, design and deploy new IT systems.

However, while the cumulative nature of IT capabilities is recognized in literature, research has rarely considered how past experience with IT innovations can actually perpetuate or hinder future IT innovations. The gap in our understanding remains despite a number of studies on how organizational learning perpetuates or hinders repeated execution of similar managerial decisions such as acquisitions (Haleblian et al. 2006) and outsourcing contracts (Whitaker et al. 2010). While this rationale is intuitively applicable in an IT context the precise mechanism of how organizational experience from past IT innovations triggers future innovations is unclear. On the one hand, it is known that organizations mindfully assess the outcomes of prior IT innovations before engaging in future ones (Levinthal and Rerup 2006; Sambamurthy et al. 1993; Swanson and Ramiller 2004); on the other hand, it is highly possible that organizations simply acquire momentum in their innovation decisions (Miller and Friesen 1980; Miller and Friesen 1982) because of the “preference-enhancing” potential of organizational experiences. Thus, while both the theoretical mechanisms -- how organizational momentum in IT innovations, and managerial assessment of their outcomes -- impact the future IT innovation decisions, this study addresses the challenge of empirically analyzing the differential effect of each.

Apart from IT innovations, which are central to enterprises’ information processing infrastructures (Radhakrishnan et al. 2008; Weill et al. 2000; Zmud 1984), equally important to firms, if not more, are product and process innovations. Organizations often improve existing business products and processes or introduce new ones, for a variety of strategic reasons, such as to capture a larger market share, compete with rivals or generate product and process efficiencies (Nelson and Winter 1982; Porter 1991). As with IT innovations and consistent with the organizational literature, it is likely that prior experience with product and process innovations, which we collectively refer to as “business” innovations, also builds key capabilities that generate momentum for further business innovations (Miller and Friesen 1980; Miller and Friesen 1982). Further, though IT and business innovations are concomitant at times (Davenport and Stoddard 1994), they need not necessarily be so.

While the main objective in this study, therefore, is to understand the momentum-generating nature of cumulative experience from IT and business innovations, we also consider the inter-relationships between the two types of innovations. We consider that, because IT innovations are a substrate for business innovations (Sambamurthy et al. 2003), past IT innovation experience could be transferable to complementary contexts within organizations. This suggests that the various types of IT capabilities being
built and strengthened as a result of repeated IT innovations, could be generalized such that the learning does not simply prepare enterprises to engage in business innovations (Davenport 1993; Davenport et al. 2004; Sambamurthy et al. 2003) but also increases their proclivity to do so. Therefore, our research questions also recognize the interdependency between IT and business innovations, and the potential effect that one type of experience may have on the innovation decision of the other. In other words, we ask: how does an organization’s prior experience with IT innovations influence its future decision to engage in both, IT and business innovations? Similarly, we also ask: how does prior experience with business innovations influence organizations’ future decision to engage again in IT and business innovations?

Finally, while we recognize momentum as a key driver of innovation decisions, our study would remain incomplete if we fail to account for the impact of performance feedback. As mentioned earlier, performance feedback (Greve 2003; Levitt and March 1988) has been recognized as a critical learning mechanism where the outcomes of prior decisions can either correct or accelerate organizational momentum along a constrained trajectory. Thus, organizations do not simply get “carried away” by their experiences and innovate mindlessly (Swanson and Ramiller 2004), but instead incorporate the feedback from their prior IT innovations into their current innovation decisions. The literature is mixed on the impact of performance feedback: some find that it may facilitate future innovations while others (Leonard-Barton 1988; Wang and Ramiller 2009) find that it may, in fact, act as a restraint. Thus, our third and final research question is: how does the performance assessment of a recent IT innovation influence organizations’ future decisions to engage in IT innovations?

We examine our research questions using a unique, longitudinal data set involving a large, representative sample of 2,312 workplaces complied by Statistics Canada that contains a rich set of information on a variety of organizational variables. We develop two models of which the first is a binary probit model of the decision to engage in an IT innovation, a binary variable; while business innovation decisions, a continuous variable, is modeled using a simple regression approach. Both models account for firm level heterogeneity. We find that IT innovation experience has a significant, positive effect on IT innovation decisions – and business innovation experience has a significant, positive effect on business innovation, both findings suggesting the momentum-generating effect of innovation experience. More interestingly, IT innovation experience is found to have a significant impact on business innovation. Further, the perceived performance of existing IT innovations had a negative impact on IT innovation decisions – suggesting that greater performance tempers an organization’s incentive to implement new IT. That is, performance feedback seems to be tempering the organizational momentum created by prior experience.

Thus, our research deepens our understanding by quantifying the impact of prior innovation experience on future innovation trajectory of organizations.

The rest of the paper is organized as follows. In section 2, we provide a comprehensive review of the relevant literature and link it to proposed hypotheses. In section 3, we describe the data and the organizational measures including several control variables, while in section 4, we provide details of the model and discussion of the results and limitations. Finally, in section 5, we conclude the paper with the implications and contributions of our study and directions for future research.

RESEARCH MODEL

The organizational learning literature offers a useful theoretical basis for understanding the role of experiential learning in IT and business innovations in stimulating future innovations. Organizational learning is defined in a number of ways that suggest how it may direct future preferences for specific action at the exclusion of others. It is defined as “routine based, history dependent, and target-oriented” that is, organizations learn by “encoding inferences from history into routines that guide behavior” (Greve 2003; Levitt and March 1988). Furthermore, tacit and formal organizational routines are independent of individuals, hence, capable of surviving over time and maintaining lessons of experience, accessible by and transmittable to others, recordable in collective memory, and changeable, depending on the outcomes and targets (Levitt and March 1988). Alternately, organizational learning is “an organizationally collective learning process in which individual and group based learning experiences concerning the improvement of organizational performance and/or goals are transferred into organizational routines, processes, and structures, which in turn affects the future learning activities of the organization’s members” (p. 338, Levitt and March (1988)). Moreover, Argote (1999) views
organizational learning as associated with systematic changes in behavior or knowledge of organizations due to their experience. These characterizations of organizational learning can be summarized as follows. First, experience is central to knowledge generation and learning in organizations (Holmqvist 2003; Schilling and Kluge 2009). Second, past and existing organizational practice facilitate organizational learning by building capabilities which are encoded in organizational routines (Holmqvist 2003). Third, accumulated organizational learning processes can change the behavior of organizations over time (Holmqvist 2003) or it can constrain it along specific learning trajectories (Cohen and Levinthal 1990).

In our theorizing we will explain how all of the above characterizations of organizational learning apply to both, IT and business innovations. This suggests that this perspective is directly relevant for understanding how momentum is generated in the adoption of such innovations. The theory development in the following sections contributes by going beyond simply linking IT or business innovations with organizational learning, to explaining how past experience with these innovations should influence future ones.

**Hypotheses**

**Cumulative Experience in IT and Business Innovations**

The notion that when organizational actions are repeated, they become self-reinforcing, finds its roots in the literature on evolutionary change (Nelson and Winter 1982) and organizational momentum (Ginsberg and Baum 1994). Momentum is considered a pervasive force in organizations such that firms with a propensity to innovate continue innovating just as those who execute a strategic action in the past repeat similar ones in the future (Miller and Friesen 1980). A key explanation is that organizational routines (Feldman 2000; Levitt and March 1988; Nelson and Winter 1982; Pentland and Rueter 1994) developed during the introduction of a certain type of change or introduction of an innovation, tend to become refined by repetition. Each time the routines are executed, the organization increases its competency in them and thus, cognitively, links it with organizational performance (Ginsberg and Baum 1994). Thus, while routines become a repository for organizational capabilities, and are recurrent, they also undergo adaptation and improvement every time they are executed (Cohen et al. 1996). This process of leaning from first-hand experience is more specifically termed as “learning-by-doing” (Argote and Eppe 1990; Greve 2003). Borrowing from the above literature, IT innovation capabilities can be viewed as a set of “change routines” where each IT implementation results in a newer IT artifact being adapted to existing or redesigned task through a multi-stage implementation process.

An important aspect of organizational learning is that repeated experiences not only result in the refinement of routines, but also shape future preferences. For example, it is argued that past experience with acquisitions is a key driver of future acquisition behavior as prior acquisition experience leads firms to place greater emphasis on this mode of organizational growth than by internal expansion which then triggers future acquisitions (Haleblian et al. 2006). Similarly, repeated alliance formations (Gulati 2007; Lorenzoni and Lippariani 1996) lead firms to develop and refine relevant routines that help them understand partner competencies, assess partner intentions, and other opportunities through their partners (Gulati 1995). These routines not only help firms strengthen and generate greater value from their existing alliances (Lorenzoni and Lippariani 1996) or enter into more alliances with the same set of partners (Gulati 1995; Gulati and Gargiulo 1999). Therefore, greater alliance experience causes firms to favor this mode of organizational growth over horizontal or vertical integration, resulting in an increased propensity to strike alliances in the future. Similar evidence regarding the perpetuating nature of experience has also been found for business process outsourcing (Whitaker et al. 2010).

Experience is central to knowledge generation and learning with organizations in the context of IT implementations (Argote 1999; Attewell 1992; Dixon 2000; Fichman and Kemerer 1997; Fichman and Kemerer 1999). The cumulative nature of IT innovation capabilities and their performance impact on organizations is well-recognized in the literature (Bharadwaj 2000; Bhatt and Grover 2005; Dierickx and Cool 1989; Mata et al. 1995; Sambamurthy et al. 2003). Recent studies also illustrate how routines underlying systems development capabilities acquired in ongoing IT projects can be documented, refined and reused in future projects (Garud and Kumaraswamy 2005; Robert et al. 2008). This involves not only single-loop learning but (Argote 1999) but also double-loop learning (Argyris and Schön 1978) where firms contemplate on aspects of various IT projects that were, and were not, executed to satisfaction with
the intention of refining these routines in the future (Newell et al. 2006). Thus, the mechanisms that facilitate this reflection are project reviews (Newell and Edelman 2008), knowledge management systems (Stein and Zwass 1995), and other structural mechanisms (Hansen 2002), that lead to the accumulation of knowledge and skills pertaining to IT innovations. For example, Motoyama (2006) explains how one organization improved its software development practices over a series of 16 development projects, each time improving its documentation routines, testing, risk assessment and other procedures. Another study (Garud and Kumaraswamy 2005), describes how Infosys engages in learning-by-doing by having its employees document software development practices as well as customer interactions in different cultural contexts. This knowledge helps it to lower its effort of reproducing and improving these practices as well as the effort of targeting customers in similar cultural contexts. As another example, business process outsourcing consists of a complex set of activities such as evaluating market options, internal IT requirements, internal coordination among stakeholder teams, crafting outsourcing deals and managing relationships (Barthelemy 2001; Lacity and Willcocks 1998). Potential outsourcing client-firms develop and refine routines to execute each of these activities which lead them to enter into more deals for outsourcing a wider range of activities (Whitaker et al. 2010). IT implementation capabilities thus aggregate learning in a cumulative fashion which not only augments their IT capabilities but also increases their proclivity to engage in more implementations. Thus,

\( H1a: \) Higher cumulative experience with IT innovations increases the likelihood of future IT innovations.

Similarly, improvement in, or development of new products and processes, that is, business innovations, constitute a mainstream activity for organizations. A number of capabilities are learned during product development, such as market sensing, order fulfillment and customer linking (Day 1994; Sinkula et al. 1997). Experience plays an important role in acquisition of these capabilities and in firms’ constrained progress on their innovational trajectory. For example, Danneels (2003) explains how firms are constrained in their choices by selective refinement of customer interaction routines such that they acquire information only about a select target segment. The richer information leads them to greater success in capturing the target segments with newer or improved products, although, beyond a point, their growth becomes constrained.

However, whereas product innovations are aimed to increase market share, revenue, and compete with rivals, process innovations are aimed to generate efficiencies in coordination within and between functional areas (Clark and Stoddard 1996; Davenport 1993; Davenport et al. 2004; El Sawy et al. 1999). For example, organizations nurture capabilities that help to more accurately capture market needs, quickly redesign existing products or design new ones (Helfat and Raubitschek 2000; Hurley and Hult 1998), or to efficiently coordinate work-flow among sub-units (Adler 1995; Barney 1991; Van de Ven et al. 1976). Repeated engagement in process or product innovations builds dynamic capabilities that help organizations engage in second-order learning (Argyris and Schön 1978). By being able to repeatedly reflect on their weaknesses, benchmark their new product development processes and process performance, organizations are better able to develop greater competencies in innovating. The momentum generated by repeated business innovations is sustained particularly because organizations cognitively link it with success (Levitt and March 1988). Thus, we propose,

\( H1b: \) Higher cumulative experience with business innovations increases the level of business innovations in the future.

**Complementarity**

IT and business innovations belong to distinct domains because IT innovations pertain to adapting the IT artifact to business needs and vice versa, whereas business innovations pertain to adapting products and services to the needs of the marketplace. Therefore, routines and capabilities pertinent to each domain of innovation may have different origins and achieve different immediate outcomes for an enterprise. However, IT and business innovation capabilities overlap in critical ways because IT is the infrastructure for most business activities (McGrath and Iansiti 1998; Zuboff 1988). IT innovations support innovations in products and processes through automation, informating, or transformation (Davenport 1993; Zuboff 1988) and thus are complementary organizational changes. Therefore, the process of implementing IT innovations has substantial similarities to new product development (NPD). For example, Namibisan (2003) explains how NPD requires firms to develop four types of internal capabilities – process
management, project management, information and knowledge management, and finally, collaboration and communication. We note that each of these capabilities is also important even for engaging in IT innovations which points to the possibility that capabilities developed in the domain of IT innovation, can replicate and evolve sufficiently (Zollo and Winter 2002) such that they create a momentum for business innovations. The organizational context facilitates transfer of practices, in say, project management nurtured from multiple IT innovations over the years (Szulanski 1996), to sub-groups involved in new product development or process reengineering. For example, requirements assessment during IT implementation requires coordination with a variety of stakeholders just as product requirements are assessed during new product development. Repeated introduction of IT innovations cultivates routines to efficiently and accurately assess business needs (Chan and Reich 2007; Reich and Benbasat 2000), which helps organizations adapt its business processes. Greater IT innovation experience affords an organization the ability to use IT to achieve relevant strategic objectives, among which product and process innovations are the most likely candidates. IT innovation experience is thus suggestive of dynamic capabilities (Sambamurthy et al. 2003; Zollo and Winter 2002), and gives an organization greater confidence in improving its competitive advantage and performance by deploying IT innovations. Therefore, greater amount of such experience in IT innovations can spill over to perpetuate parallel innovations in products and processes. Experience with IT (business) innovations thus can also translate into greater momentum in business (IT) innovations because managers link the innovation-related practices cognitively to success. In a narrower contexts, such spillovers were observed in the adoption of distinct set of practices in different domains but confirming to similar institutional logic of governance (Shipilov et al. 2010). Similarly, formal employee evaluation practices triggered adoption of formalized employee evaluation and pay grade practices (Baron et al. 1986) which suggests that ‘innovation practices’ can spill over from the IT domain to the business domain.

In summary, we hypothesize two types of interdependencies as in H2a and H2b. However, the theoretical argument for H2a is stronger than for H2b. This is because product and process innovations are externally oriented to satisfy strategic needs, whereas IT innovation managers face a bigger constituency: IT innovations need to satisfy not only internal users, but also achieve the strategic objectives for such IT investments. Therefore, the degree to which business innovation experience can be brought to bear to stimulate IT innovation may not be as high as the extent to which IT innovation experience can stimulate business innovations.

\( H2a: \) Higher cumulative experience with IT innovations increases the level of business innovations in the future.

\( H2b: \) Higher cumulative experience with business innovations increases the likelihood of IT innovations in the future.

Perceived Performance Improvements and IT innovations

The proposition, that momentum drives an organization to commit itself to repeating past actions, does not imply that there is no mechanism to restrain or change momentum. Indeed in some instances, firms have been shown to transition from periods of momentum to stasis or reorientation, whereas in others, momentum has led to eventual failure (Kelly and Amburgey 1991). A substantial amount of research shows that organizations can learn from both, their failures and successes, and thus correct or reduce momentum in potentially fatal directions (Greve 2003; Lampel et al. 2009; Schwab and Miner 2008). Thus, reinforcement mechanisms play an important role in directing organizational learning (Cyert and March 1963; Lant et al. 1992; Levitt and March 1988).

It is suggested that past successful decisions or experiences increase faith in the underlying organizational knowledge and decision making processes and thus creates the proclivity to continue with status quo (Amburgey and Dacin 1994). Interestingly, the perception of the success of past decisions does not always create a positive reinforcement mechanism (Beck et al. 2008). In fact, some literature suggests that instead of providing positive reinforcement, developing competencies is concomitant with establishment of path dependent rigidities (Danneels 2003). Therefore, success in past decisions or experiences can actually discourage innovative behavior in the future whereas failure can encourage it because failures trigger a higher level of communication and introspection than successes do (Homsma et al. 2009; Nelson and Winter 1982; Rerup 2009). This implies that for organizations that are able to survive, failure episodes provide more learning opportunities than do successes (Lampel et al. 2009).
With respect to IT innovations, we propose that it is the failure, instead of success, with prior IT innovations that contributes to the momentum to engage in another IT innovation in the future. Conversely, success with prior IT innovations should temper the momentum and thus reduce the proclivity to engage in future innovations. We make this argument considering that IT is often regarded as an internal resource that needs to be in-place (a “competitive necessity” (Clemons and McFarlan 1986)) by managers rather than a strategic choice or a driver of growth instead of as a critical driver of competitive success. Thus, managers are likely to be satisfied and refrain from making more IT investments if they perceive prior investments are successful, so that they can direct their resources at competing in the market-place (Goh and Kauffman 2011). Conversely, managers are more likely to be reactive engaging in more IT innovations when a prior IT innovation is perceived to be a failure. Thus, our final hypothesis proposes that organizations’ perceived success in recent a IT innovation should deter future IT innovations.

\[ H3: \text{A positive performance outcome from the most recent technology implementation decreases the likelihood of IT innovations in the future.} \]

**DATA**

We use the data generated by the Workplace and Employee Survey (WES) which was conducted over the period 1999 to 2006 by Statistics Canada. The objective of this survey is to collect organizational level information from Canadian businesses. The survey provides researchers with a unique opportunity to study competitiveness, innovation, technology use, organizational change, and human resource management at the workplace level. The sample frame of WES was generated based on Statistics Canada’s Business Register, and focuses on organizational locations (workplaces) with active employees. These criteria were used by Statistics Canada to stratify the sample industry (n=14), region (n=6), and organizational size (based on estimated employment categories of small (0-19), medium (20-99), and large (greater than or equal to 100)). Organizations were followed up to four or more years with new workplaces being added each year to replace non-responding workplaces. In all, the WES dataset provides longitudinal data on workplaces over a maximum of eight years. Thus, the data is unique and is representative of all the workplaces in Canada.

The data collection process for the WES consists of two steps. First Statistics Canada sends a copy of the survey to each of the workplaces so that the respondents have time to review their records and find all the information that this comprehensive survey asks for. In the second step, one manager from each of the workplaces completes the questionnaire during a personal interview which is conducted by a staff member of Statistics Canada. The Statistics Act of Canada strictly ensures the confidentiality of these responses. The data from the survey are first validated and verified, then adjusted where necessary, and finally evaluated to ensure their quality. Statistics Canada applies various rules to prevent the release of any confidential information and where necessary, suppresses the identifiable data. The response rates for this survey therefore ranges from 95.2% to 74.9% from 1999 to 2006. In addition, a sampling weight is associated with all the sampled units to obtain estimates for the population in the WES. The WES data has been used in the literature to address a broad range of questions from determinants or organizational absenteeism (Dionne and Dostie 2007), to the effect of layoffs on the relationship between high-involvement work practices and productivity (Zatzick and Iverson 2006), to strategic purity and its effect on superior performance (Thornhill and White 2007), and finally to whether or not computer use generates a wage differential (Dostie et al. 2009).

**Initial Sample.** For the purpose of this study, we create a longitudinal dataset obtained by pooling all the workplace-level observations from 1999 to 2006. From the merged dataset we drop those which have smaller than 20 employees and are not-for-profit. Further, since the main variable of interest in this study is whether or not workplaces adopted a new computer software or hardware or whether or not a workplace adopted a new business innovation in each year, and because not all workplaces answered this question, the initial sample excluded these observations. The initial sample was then trimmed as explained next to create the final balanced panel of 2312 workplaces.

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1 The data in WES are confidential and housed in Statistics Canada’s Research Data Centres (RDCs).
Measures

In this section, we provide a description of the variables used in our analysis. We start with a description of our two dependent variables: IT innovation (ITINNOV) and business innovation (BINNOV), followed by a description of the independent variables, including several control variables.

Dependent variables

IT innovation (ITINNOV). This variable represents whether or not a workplace adopted a major new software in any given year. This does not include software upgrades in that year. This variable is binary such that it is 1 when a workplace adopts a new IT in a year and 0 otherwise.

Business Innovation (BINNOV). There are four organizational innovativeness variables in the dataset. These include whether or not workplaces introduce (a) any new processes in a year, (b) any new products and services in each year, (c) any improved processes in a year, and (d) any improved products and services in a year, where 1 implies “yes” and 0 implies a “no”. By summing the responses across all the four items, we created a continuous measure of the degree of business innovation in a workplace in a given year. Thus, a higher value of BINNOV implies a higher degree of innovativeness, the maximum value this variable can take being four, the minimum zero.

Independent Variables

Cumulative Experience with IT Innovations (CEITINNOV). This variable represents a workplace’s prior experience with business innovations and is created by summing the ITINNOV variable for a workplace in prior years. The higher the value of this variable, the more frequently the workplace has engaged in IT innovations in prior years.

To operationalize CEITINNOV, we start by defining a pre-calibration period with the objective of initializing CEITINNOV. This ensures that the variable stabilizes before it is used for calibration purposes. This approach has been used extensively in the empirical work in marketing studies which require computation of households’ “inventory” for a particular product with the objective of predicting their purchase decisions (Ailawadi and Neslin 1998; Gupta 1988). We identify the pre-calibration or “initialization period” as follows: since we have eight years of data (1999-2006), we use the first three years (1999-2001) as this initialization period. Thus, the years 2002 – 2006 are used as the calibration dataset to estimate the model. We drop all workplaces that had only one observation during this three year period and those firms who leave the panel on or after 2001, leaving us with 2,312 workplaces. Note that since we use the first three years, 1999-2001 to initialize the CEITINNOV and CEBINNOV variables, all organizations in the dataset can have a maximum of five observations. We use a balanced panel approach by taking only those workplaces which are present for all five years of the calibration dataset. This leaves us with 9,350 observations across 1,870 workplaces. None of the workplaces drop out and then re-enter the panel. For these workplaces, we then compute the CEITINNOV for organization i for our initial year 2002 as:

\[ CEITINNOV_{i,2002} = ITINNOV_{i,2001} + ITINNOV_{i,2000} + ITINNOV_{i,1999} \]  

Once CEITINNOV is defined for the first year of the calibration period, we can define CEITINNOV for all subsequent years as:

\[ CEITINNOV_{i,t} = CEITINNOV_{i,t-1} + ITINNOV_{i,t} \]  

While the actual survey question pertained to the “implementation of a new computer software or hardware (not an upgrade)”, we used the following criteria to identify those workplaces implementing business functional software in the following manner. We examined a variable captured in the WES dataset that indicates the category of employees using the new IT. If only only ‘technical’ workers using the new IT, it would indicate that the implementation was either a new hardware or a technical component that has no bearing on the functional applications. Examples of such components are a new operating system or an software antivirus module. None of the workplaces reported only technical workers using the new technology but had other employee categories such as trades, sales employees also using the new IT. This implied that all our observations pertained to functional software.
Cumulative Experience with Business Innovations (CEBINNOV). This represents a workplace's prior experience with business innovations and is created by summing the BINNOV variable for the same workplace in years prior to the current year. The higher the value of this variable, the more frequently the workplace has engaged in one of the four types of business innovations. Like CEITINNOV, we also use the initial three years of the panel to initialize this variable and to predict CEBINNOV in the initial year for workplaces that enter the panel in or after 2001.

IT Performance Feedback (EFFECT). The survey also asks the workplaces whether the implementations of the particular technology had a negative (-1), neutral (0), or positive (+1) effect on their profit margins, quality of product/service, technological capabilities, working conditions, lead time, range of products/services, labor requirements, energy requirements, capital requirements, material requirements, and design costs. We add these values to create a summated scale for perceived effect (EFFECT) of the adoption of the new IT innovations on organizational performance.

Control variables

Industry (INDUSTRY). We segregate the industry a workplace belongs to into two categories - manufacturing and the service – to create a binary indicator variable. Manufacturing refers to several industries, including forestry, mining, oil and gas extraction, labor intensive tertiary manufacturing, primary product manufacturing, secondary product manufacturing, capital intensive tertiary manufacturing, construction, and communication and other utilities. The services industry refers to industries such as transportation, warehousing, wholesale, retail trade and consumer services, finance and insurance, real estate, rental and leasing operations, business services, education and health services, and information and cultural industries. Service industries are understood to have high information intensity compared to manufacturing industries. Size of Organization (SIZE). The size of a workplace can have an impact on innovation choices either because of greater resources possessed by large organizations facilitates more innovations; or lower agility can hinder them. We therefore control for a workplace's size in our analysis. This variable is operationalized as the log of the total number of employees in each workplace. Lack of Skilled Personnel (LACKSKILL). We also control for lack of skilled personnel which can be an impediment for adoption of innovations in organizations. This is a dichotomous variable that indicates whether this factor is an impediment to implementation of new technologies in the workplace.

Computer Use (COMPUSE). We divide the number of employees who use computers as part of their normal working duties within workplaces by the total number of employees to create this variable. The higher the value of this variable is, the higher is the average rate of computer use within organizations. This captures the notion that a higher rate of computer usage should facilitate both IT and business innovations. Competition (COMPETE). We also control for competitive effects as suggested by Sarmiento and Wilson (2005) in their study of technology adoption. In other words, IT and business innovation decisions may simply be a response to the competitive environment – more competition may spur greater investment. In the survey, a binary question that asks whether workplaces face direct competition from locally, Canadian, USA, or internationally-owned firms is used to operationalize competition. We consider the value of this competition variable to be 1 if workplaces face competition and 0 otherwise. Other questions ask for the level of competition in each case. We create a weighted average competition variable based on these information which ranges from 0 to 1. The higher the value of this variable is, the greater is the extent to which workplaces face competition. Cumulative IT Training (CUMITTRNG). We also control for IT training. There are four binary software and hardware training variables in the dataset. These include (a) whether or not workplaces pay for or provide employees with classroom training for computer software, (b) whether or not workplaces pay for or provide employees with classroom training for computer hardware, (c) whether or not workplaces pay for or provide employees with on-the-job training for computer software, and (d) whether or not workplaces pay for or provide employees with on-the-job training for computer hardware. We consider the value for each of these variables to be 1 when the training was provided and 0 otherwise. We then create a summated scale for IT training by weighing all four items equally. The higher the value of this variable is the higher is the intensity of IT training. CUMITTRNG was then created by summing the yearly IT training variable for the same workplace in years prior to the current year.

Finally, we also control for time specific effects by including year dummies. Since the period of analysis is from 2002 – 2006, we have 4 time dummies running from 2003 – 2006. Table 1 presents the univariate
statistics and correlations, which suggest that any concern about multi-collinearity is mitigated by the low correlations.

| Table 1: Descriptive Statistics |
|---------------------------------|-----------------|-----------------|-----------------|
|                                 | Mean    | StdDev | Mean   | StdDev |                  |
| Control variables               |         |        | Model variables |        |                  |
| INDUSTRY                        | 1.72    | 2.31   | ITINNOV          | 1.45    | 4.50             |
| SIZE                            | 4.03    | 3.66   | BINNOV           | 1.38    | 8.04             |
| COMPUSE                         | 0.46    | 1.81   | CEITINNOV        | 1.40    | 6.40             |
| COMPETE                         | 7.42    | 23.45  | CEBINNOV         | 8.11    | 29.88            |
| CUMITTRNG                       | 5.71    | 25.69  | EFFECT           | 0.89    | 11.18            |
| LACKSKILL                       | 0.24    | 1.8    |                  |         |                  |

**MODEL AND ANALYSIS**

In order to test our hypotheses, we develop two econometric models – the first links IT innovation decisions to past IT and business innovations, while the second model characterizes the influences on business innovation decisions.

**IT Innovation.** Since the dependent variable, ITINNOV is a binary variable, we use a binary probit model to capture the probability that an organization engages in IT innovation. As per our hypotheses, this probability is a function of both past cumulative IT and business innovations as well as IT performance feedback. Furthermore, we consider the mixed version of the binary probit which allows us to incorporate heterogeneity across certain parameters in the model (Train 2009). In particular, we model the intercept term as a random variable. In order to specify the model, let \( Y_i \) be a random variable which takes on a value of either 0 or 1 at time \( t \), where 1 represents the decision that firm \( i \) engages in an IT innovation. Let \( \beta \) be a vector of coefficients which follow a distribution, \( \beta \sim g(\theta) \) where \( \theta \) are the parameters of the distribution of the \( \beta \)'s over the population. Then, conditional on \( \beta \),

\[
Pr(Y_i = 1 | \beta) = F(\beta_0 + \beta_1 CEITINNOV_i + \beta_2 CEBINNOV_i + \beta_3 EFFECT_i + \beta_4 BINNOV_i +
\]

\[
+ \beta_5 CEITINNOV_i^2 + \beta_6 CEBINNOV_i^2 + \sum_{i=1}^{K} \beta_i Z_i)
\]

where \( F(.) \) is the cumulative distribution function. By assuming that \( F(.) \) is the normal CDF, we are able to derive the probit model. Note that to account for a non-linear functional relationship between organizational momentum and both dependent variables we also include squared terms for CEITINNOV and CEBINNOV. The organizational learning literature typically considers a quadratic effect of learning on future outcomes because of a saturation effect, where beyond a threshold, the experience or learning ceases to have an impact on the outcome, in this case ITINNOV (Argote 1999). We also include BINNOV as an explanatory variable to control for the concurrent nature of IT and business innovations. \( Z_i \) represents the vector of control variables discussed in the previous section.

The unconditional probability is then obtained by integrating over the density of \( \beta \):

\[
Pr(Y_i = 1) = \int Pr(Y_i = 1 | \beta) g(\beta | \theta) d\beta
\]

**BINNOV.** Our other dependent variable, business innovation, BINNOV, on the other hand, is operationalized as a continuous variable. We therefore use an ordinary least squares regression technique to examine this scale dependent variable. We account for heterogeneity across firms by estimating a random effects models (Greene 2000). Therefore, our model for BINNOV is given by:
\begin{align*}
\text{BINNOV}_i &= \gamma_i + \gamma_{i1} \text{CEITINNOV}_i + \gamma_{i2} \text{CEBINNOV}_i + \gamma_{i3} \text{EFFECT}_i + \gamma_{i4} \text{ITINNOV}_i + \\
&+ \gamma_{i5} \text{CEITINNOV}_i^2 + \gamma_{i6} \text{CEBINNOV}_i^2 + \sum_{i+6:k<K} \gamma_k Z_{it} + u_i
\end{align*}

(5)

where \( u_i \) is i.i.d \( N(0,1) \) and \( \beta \)'s are independent random draws from a normal distribution, \( N(0,\sigma^2_\beta) \). Again, we also include ITINNOV as an independent variable to control for the concurrent nature of BINNOV and ITINNOV and the square terms to account for any non-linear relationships, while \( Z_{it} \) represents a vector of control variables.

**RESULTS**

Tables 2A (ITINNOV) and 2B (BINNOV) present the results of our analyses for a number of incremental models for each of the dependent variables. In what follows, we report the incremental results separately for our two dependent variables separately.

**IT INNOVATION as a dependent variable**

In Model 1, we explore the impact of CEITINNOV. We find that, consistent with our Hypothesis 1a, cumulative IT innovation experience has a positive and significant effect on an organization’s decision to invest in IT. Model 2 adds CEBINNOV in order to examine complementarity between IT innovation and business innovation experience, but contrary to our hypothesis (H2b), the impact of CEBINNOV on the probability to engage in IT innovation was negative. In Model 3, we add IT performance feedback (EFFECT). We find support for Hypothesis 3: the coefficient for EFFECT was negative (\(-0.169\)) and significant, indicating that a positive feedback can actually inhibit the inclination to engage in IT innovations. In our final model, Model 4, we add the square terms for CEITINNOV and CEBINNOV to account for any non-linear relationships – the results were consistent with the previous model, except that CEBINNOV is no longer significant. Furthermore, we find that while the square term for CEITINNOV was significant, that of CEBINNOV was not. Finally, we do not find BINNOV to be significant indicating a lack of support for the concurrency of IT and business innovation decisions.

**BUSINESS INNOVATION as a dependent variable**

For BINNOV, in Model 1, we explore the impact of CEBINNOV and find that, consistent with our Hypothesis 1a, cumulative business innovation experience has a positive (0.027) and significant effect on the extent to which organizations engage in business innovations. Model 2 adds CEITINNOV: we find evidence of complementarity between IT innovation and business innovation experience, thus finding support for H2a (0.132). In the final model, Model 3, we add the two square terms for ITINNOV and BINNOV, of which only the square term for BINNOV was significant (\(-0.023\)). All of the remaining results are consistent with the previous models. Finally, contrary to the model for ITINNOV, we find evidence of concurrency between ITINNOV and BINNOV as the coefficient for ITINNOV is positive (0.334) and significant. A discussion of these findings follows in the subsequent sections.

**Limitations**

The findings of this study however need to be interpreted in the light of its limitations. First, the vast literature on literature on organizational learning suggests an equally large set of measures of organizational learning many of which involve direct measurement of learning possibly through survey questionnaires and qualitative data collection. The archival data on establishment level data and its confidentiality precludes us from a direct measurement of the theoretical mechanisms proposed in this study. This however sets the stage for qualitative work in this domain to understand the role of experiential learning by organizations in stimulating IT and business innovations. Second, we were unable to use the more robust estimation approach of workplace-level fixed effects because of the short
duration of the panel: for each organization we have only five observations. However, we do account for firm level heterogeneity by incorporating random effects. Third, more precise theory development could have been facilitated with a longer panel that would permit usage of duration models as utilized in recent work (Haleblian et al. 2006) to understand the effect of experience on repeated execution of similar managerial decisions.

Table 2 – Estimation Results

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>A. Prob(IT Innovation) ITINNOV</th>
<th>B. Business Innovation BINNOV</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Models →</strong></td>
<td>1    2   3   4</td>
<td>1    2   3</td>
</tr>
<tr>
<td>Industry (INDUSTRY)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Size (SIZE)</td>
<td>-.714 (.338) -.686 (.346) -.668 (.374) -.456 (.393)</td>
<td>.222 (.044) .217* (.044) .199* (.045)</td>
</tr>
<tr>
<td>Lack of Skilled Personnel (LACKSKILL)</td>
<td>-.393 (.266) -.385 (.230) -.176 (.239) -.287 (.291)</td>
<td>.145 (.087) .138 (.086) .127 (.084)</td>
</tr>
<tr>
<td>Computer Use (COMPUSE)</td>
<td>.558 (.597) -.424 (.065) -.083 (.065) -.357 (.382)</td>
<td>.351 (.249) .345 (.247) .327 (.243)</td>
</tr>
<tr>
<td>Competition (COMPETE)</td>
<td>-.015 (.036) -.005 (.036) -.002 (.034) -.008 (.031)</td>
<td>-.000 (.008) -.000 (.008) .001 (.007)</td>
</tr>
<tr>
<td>Cumulative IT Training (CUMITTRNG)</td>
<td>-.099 (.063) -.061 (.065) -.083 (.066) -.074 (.055)</td>
<td>-.011 (.013) -.006 (.013) .005 (.013)</td>
</tr>
<tr>
<td>IT Innovation Experience (CEITNNOV)</td>
<td>3.358* (.259) 3.519* (.240) 3.768* (.246) 7.132* (.627)</td>
<td>.132* (.042) .114* (.022)</td>
</tr>
<tr>
<td>Business Innovation Experience (CEBINNOV)</td>
<td>-.148* (.052) -.135* (.055) -.017* (.111) -.027* (.009)</td>
<td>.019 (.010) .239* (.108)</td>
</tr>
<tr>
<td>Performance Feedback (EFFECT)</td>
<td>-.169* (.035) -.232* (.044)</td>
<td>7.132* (.627) -.023 (.023)</td>
</tr>
<tr>
<td>IT Innovation Experience²</td>
<td>7.132* (.627) -.0174 (.111)</td>
<td>.027* (.009) .019 (.010)</td>
</tr>
<tr>
<td>Business Innovation Experience²</td>
<td>-.0174 (.111)</td>
<td>-.004* (.001)</td>
</tr>
<tr>
<td>IT Innovation (ITINNOV)</td>
<td></td>
<td>.452 (.105) .361* (.101)</td>
</tr>
<tr>
<td>Business Innovation (BINNOV)</td>
<td>.180* (.063) .0115 (.065) .114 (.067) .121 (.072)</td>
<td>42652 42621 42522</td>
</tr>
<tr>
<td>AIC</td>
<td>97201 95206 90487 74489</td>
<td>92652 42621 42522</td>
</tr>
<tr>
<td>Total Observations</td>
<td>9350 9350 9350 9350</td>
<td>9350 9350 9350</td>
</tr>
</tbody>
</table>

3 We also estimate the two models using fixed effects, but the Hausman test indicates that the random effects model is the more appropriate one.
DISCUSSION AND IMPLICATIONS OF RESULTS

Adoption of IT innovations nurtures organizational capabilities for searching, acquiring, localizing, and assimilating new IT artifacts, and these capabilities get refined from repeated execution during newer IT implementations. Similarly, adoption of process and product innovations nurtures capabilities for searching for external information, acquiring resources, and localizing, and assimilating new practices and technologies. Similar to IT innovations, business innovation capabilities also get refined by repeated execution as per what the learning-by-doing literature suggests. This study contributes to the understanding of how experiential learning accumulated from repeated IT innovations in the past increases organizational proclivity to engage in more innovations. Our analysis of 2,300 Canadian workplaces over a span of 8 years finds support for most of our hypotheses of which the more interesting ones are those (H2a, H2b and H3) that refine the theoretical argument of learning-by-doing by considering two facets of the IT context. First, experiential learning from IT innovations can not only lead to a greater propensity for more IT innovations, but it can also spill over to facilitate business innovations. These are significant findings that have never been studied in IS research, which has mostly assumed that past experience builds IT capabilities that are only potentially re-deployable towards future innovations. Therefore, our finding that such experience actually perpetuates more IT innovations is a significant empirical advance. Further, the twin-result that IT innovation experience also stimulates business innovation is a theoretical advance that closes a significant gap in IS theory on the innovation-enhancing nature of IT investments (Sambamurthy et al. 2003). The implications of these findings are quantified by our parameter estimates and also have policy implications for say, government subsidies towards IT investments – thus suggesting that IT innovation can perpetuate themselves from an initial boost of spending. Further, and more importantly, such subsidies can also result in an unintended benefit of stimulating business innovations. Thus, government policies aimed at stimulating IT innovations appear to have a ‘multiplier’ effect. These findings also can help decision makers within organizations make more informed decisions regarding the value of their innovation decisions because of the multiplier effect. The second implication of our study pertains to the role of feedback from prior IT innovations. The results show how a positive assessment of a prior IT implementation dissuades firms from engaging in new IT innovation. Combined with our finding that IT innovation experience stimulates business innovation, the feedback effect points to a risk that a positive managerial assessment may have an unintended negative effect of retarding new IT investments, and thus, indirectly, retarding business innovations. In other words, managers having a positive assessment of a prior IT implementation may restrain from engaging in IT innovations, more than is optimal for their organization. Thus, managers should be more aware of the indirect but strong business-innovation-enhancing effect of new IT investments and give them greater priority than before in relation to business innovation efforts. Third, the results of this study can also provide a focus for the marketing efforts of IT vendors by informing them about those organizations which are more likely to seek external IT services in the future. The results of this study show how IT intensity is path dependent and therefore, early mark-downs in technology products to customers is likely to result in greater growth opportunities for IT vendors due to the momentum generating effects of IT innovation experience.

FUTURE RESEARCH AND CONCLUSION

The research on IT implementations has focused on one-off implementations by organizations, which therefore understates the importance of the historical context. There are two major benefits of considering the historical context. One, it leads to a greater understanding of how organizational learning affects the IT innovation trajectory of organizations. Two, it affords a way to understand path dependencies (Bharadwaj 2000) and thus the origin of IT innovation capabilities. Some organizations are considered as ‘endowed’ externally or by virtue of its IT executives’ expertise with greater IT-based competitive advantage by being able to innovate faster using IT as a platform (Sambamurthy et al. 2003). This paper offers a view that both, IT- as also business- innovation capabilities emerge simply because of repeated engagement with IT and business innovations. The findings thus lay a ground work for future research in several directions. One, future work can disaggregate IT innovation capabilities into its components and the momentum-generating impact of each of such components can be studies to offer
more in-depth guidance to practitioners as well as scholars. Two, empirical research can also try to ascertain the duration for which IT innovation experience remains effective for any organization. A survey-based data collection combined with archival data can be used to better model experience effects longitudinally. Further, some organizations are better able to preserve their learning whereas others dissipate IT or business innovation knowledge because of employee turnover, excessive employee mobility across subunits and so forth. What are the optimal intra-organizational arrangements that preserve IT innovation experience and which ones accelerate business innovations to the greatest extent? Future work can also explore the performance benefits of IT and business innovation experience in terms of competitive advantage or survival. How much competitive advantage can IT innovation experience create and how long does it last? Finally, organizations learn to better engage in IT innovation not only experientially but also vicariously (Holmqvist 2003), by virtue of outsourcing arrangements (Levina and Vaast 2005), mergers and acquisitions (Tanriverdi and Uysal 2010) or mimitically (Swanson and Ramiller 2004). How can they optimally combine their experiential learning with IT innovation with vicarious learning?
References


