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STRATEGY, HUMAN CAPITAL INVESTMENTS, BUSINESS-DOMAIN CAPABILITIES, AND PERFORMANCE: A STUDY IN THE GLOBAL SOFTWARE SERVICES INDUSTRY

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Research summary: *In knowledge-based industries, continuous human capital investments are essential for firms to enhance capabilities and sustain competitive advantage. However, such investments present a dilemma for firms, because human resources are mobile. Using detailed project-level operational, financial, and human capital data from a leading multinational firm in the global IT services industry, this study finds that deliberate investments in improving general human capital can help firms develop superior capabilities and maintain high profits. This paper identifies two types of capabilities essential for success in this industry—technological and business-domain capabilities—and provides empirical evidence justifying such investments. Theoretical and practical implications of capability-seeking general human capital investments are discussed.*

Managerial summary: *The primary managerial implication of this research is that capability-seeking investments in developing general human capital through strategic learning (training and internal certifications) can enhance firm performance. Although investing in general human capital is risky, the firm considered this a strategic necessity in order to thrive in the fast paced IT services industry. By leveraging general technological skills in combination with business-domain knowledge to address customer's business problems firms can earn and sustain higher profits. Our study also demonstrates how a developing-country firm responded to strong competitive challenge from global rivals possessing superior capabilities by upgrading the capabilities of its employees through internal development. In doing so the firm was able to narrow the capability gap vis-à-vis its foreign peers and expand its business globally.*

INTRODUCTION

In today's knowledge economy, firms need to nurture their human capital continuously to gain and sustain competitive advantage (Hatch and Dyer, 2004; Mayer, Somaya, and Williamson, 2012). This is especially relevant for knowledge-based industries such as information technology (IT), in which productivity improvements related to employee skills are major determinants of performance (Bapna *et al.*, 2013; Ethiraj *et al.*, 2005; Huckman, Staats, and Upton, 2009; Mayer *et al.*, 2012). In such industries, employees' skills and competence require continuous improvements due to the fast pace of technological change (Lee,

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Trauth, and Farwell, 1995). The knowledge-based view (Grant, 1996; Kogut and Zander, 1993) conceptualizes a firm as a vehicle for the integration and application of knowledge, which resides within individuals. Becker (1962, 2003) and Mincer (1962) suggest that investment in human capital through employee training improves its quality and has major productivity implications. Consequently, understanding the performance implications of capability development through deliberate human capital investments has significant implications for both theory and practice (Lepak and Snell, 1999).

Human capital is not owned or fully controlled by the firm, because employees are free to carry their knowledge to other employers (rival firms). Therefore, this deliberate investment in human capital to enhance employees' capabilities poses a classic problem for firms' managers: their investments might turn into losses as rival firms attract top talent away by providing a better total compensation (Coff, 1997, 1999; Coff and Kryscynski, 2011). Becker's (1964) seminal work emphasizes the strategic importance of firm-specific human capital over general human capital. Building on that, Campbell, Coff, and Kryscynski (2012) forward a theory explaining that firm-specific human capital can also be valuable to other firms, since it reflects an employee's willingness and ability to invest in learning new skills. Similarly, they suggest that general human capital may be valuable to the focal firm if the labor market underestimates the true worth of employees' skills and if the focal firm is able to exploit those skills better than rivals and design inimitable compensation packages catering to employees' idiosyncratic preferences in order to retain them.

Motivated by this body of work, we undertake an empirical study of the software services industry in which we examine the performance implications of a firm's strategic learning activities (Kuwada, 1998) through investments in two types of general human capital: technological and industry domain.[1] Specifically, we seek to show how technological and industry- or business-domain knowledge can enable the development of superior capabilities with attendant benefits for performance. In doing so, we provide empirical evidence supporting Campbell *et al.'s* (2012) theory that investments in general human capital can be beneficial for firms.

First, we investigate how general human capital investments in developing two types of capabilities (technological and business domain) can enable a firm to realize its strategic objectives in the context of software services outsourcing and expand our understanding of the performance implications of investing in different types of capabilities. A recent paper by Bapna *et al.* (2013) tested the impact of general training on employee performance. However, their study did not include the effect of mandatory certification examinations on project team performance, nor did they link those investments with capability development and corporate performance.

Second, there is dearth of prior research that establishes the link between employer-provided training and internal certifications and corporate performance, which this study attempts to accomplish. This is an interesting avenue of research, because it promises to unravel the conditions under which investments in general human capital can benefit firms. Human capital theory, developed by Becker (1964) and colleagues, recommends that firms invest in firm-specific human capital and suggests that investments in general human capital are inherently risky. Our findings highlight the contribution of general knowledge to firm performance, which is an emerging research program in strategy.

Third, by employing detailed large-sample project-level data from a leading software services firm and using human capital variables to measure capabilities, this paper refines Ethiraj *et al.*'s (2005) attempts to measure project management capabilities using operational metrics.[2] Human capital measures are closer (than firm-level measures such as R&D and marketing spending) to the actual phenomenon of individual capability development, which aggregates up to project- and firm-level capabilities.

Finally, our study also provides a nonambiguous measure of organizational capabilities and empirically tests the effect of different types of human capital on disaggregated performance outcomes at the operational level within the firm, thereby addressing some of the concerns raised by Ray, Barney,

[1] While technological knowledge and skills can be used in a variety of firms in multiple industries, industry-domain knowledge and skills can be used by rival firms in the same industry. Thus, both types of knowledge and skills are general and not firm specific—technological knowledge being more general in relation to industry-domain knowledge

[2] Ethiraj *et al.* (2005) measured project management capabilities using effort overrun, schedule slippage, and in-process defects

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and Muhanna (2004).[3] Thus, this study is one of the first to use micro-level human capital variables and project-level performance outcomes to measure capabilities and to link capabilities with corporate performance. In this way, it lays the groundwork for future research that seeks to understand the impact of capability-seeking general human capital investments.

Use of firm-specific, archival, project-level human capital data provided precise measures for the key capabilities investigated in this study, which, combined with econometric analyses, facilitated robust controls for alternative explanations. Our findings have both theoretical and practical significance and, most importantly, they justify increased general human capital investments in the form of training and internal certifications to develop business-domain knowledge and augment firm capabilities in this important sector of the global economy. Overall, this study adds to contemporary research on the debate between general and firm-specific human capital and the origins of capabilities (Coff and Kryscynski, 2011; Winter, 2012) by informing scholars of the performance impact of general human capital investments aimed at capability development and their link to firm strategy.

THEORETICAL FRAMEWORK

This paper draws on the knowledge-based view and human capital framework (Becker, 1962, 1964, 2003; Castanias and Helfat, 1991, 2001; Kambourov and Manovskii, 2009; Mayer *et al.*, 2012) to examine the performance implications of human capital investments aimed at developing technological (general) and business-domain (industry specific) capabilities. Kang and Hahn (2009) analyze the performance implications of technology, domain, and methodology or procedural knowledge in software development projects. Using a similar typology, our paper examines how technological (general) and domain (industry-specific) capabilities developed by employee skill-building activities within an organization affect project performance in the context of IT services.

[3] Ray *et al.* (2004) advocated for using process level dependent variables to measure the impact of capability development, instead of using overall firm level performance outcomes

These capabilities are highly relevant for knowledge workers, because knowledge work requires the application of certain general knowledge (e.g., about technology) to solve business problems. For example, a software programmer might develop an Internet-based customer-information tracking system for a retail chain by applying general technologies such as Java, J2EE, HTML, and Oracle to an industry-specific context. This type of task would require at least two types of expertise: technological (knowledge of the software technologies involved in coding) and industry-domain (knowledge of the information flow in the retail chain's business system). Therefore, exploring the implications of investing in different types of human capital can help managers optimize their performance.

Now, we introduce two types of capabilities relevant for firms aiming to offer high value-added IT services to its customers. In the IT services sector, firms develop technology solutions that are tailored to meet the business objectives of their customers. Therefore, the first task for firms is to understand the business requirements or problems of customers and then develop a business process model or roadmap to address the issues and achieve the business objectives. This type of task requires a thorough knowledge of the industry domain of the client as well as its internal business systems architecture.

The next step is to transform the business goals into technological specifications and develop a technological solution to the business problem identified earlier using a combination of software products that can accomplish the business objectives of the client. This requires in-depth knowledge of various technologies such as Java, Dot Net, Mainframes, Oracle Databases, ERP systems such as SAP, etc. These capabilities are process oriented and more codified, especially when the process being carried out is technology intensive. Technological capabilities enable a firm to develop a product or service in an efficient and cost-effective manner. Technological capability is similar to know-how (Garud, 1997) and represents knowledge of the process by which a new technological product or service can be developed. The output from these capabilities is often a general technology that must be customized and adapted for multiple situations to achieve a variety of business goals for different buyers.

In contrast to technological capabilities, a different set of tasks and routines are required to

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customize a general technology to make it usable by a given client. Business-domain capabilities enable a firm to tailor a general technology to suit the idiosyncratic requirements of customers in a given industry sector. Business-domain capability is similar to know-why (Garud, 1997) and represents an understanding of the principles (cause-and-effect relationships) underlying a phenomenon (in this case, a customer's business in a specific industry sector). Although a firm may purchase or gain access to technology from external partners, this does not guarantee that it can readily deploy the technology in the market (Leonard-Barton, 1988; Steensma and Corley, 2000; Weigelt, 2009). Without sufficient customization, general technology may be unusable in the customer's internal business environment. To remain competitive, a firm must be good at both these capability dimensions.

This distinction between technical and business-domain capabilities is particularly relevant in high-technology services industries, where firms adopt new technologies to enhance their business processes (Weigelt, 2009). The use of such technologies often involves information-systems applications that are customer facing and must be incorporated within the firm's ongoing business processes and systems (Purvis, Sambamurthy, and Zmud, 2001) as well as embraced by its customers (Meuter *et al.*, 2005). For example, Enterprise Resource Planning (ERP) technologies are customized to suit the idiosyncratic requirements of a particular industry. Being general in nature and licensed by the software manufacturer (e.g., Oracle, SAP), they require extensive customization to fit a buyer's existing systems for proper utilization and realization of expected business benefits. Such business-domain capabilities are not fungible across different industries, since these services involve a high level of tailoring to the client's business environment and industry systems architecture.[4] This is where vendor firms add value to the product or service and can earn higher profits.

To summarize, technological capabilities enable a firm to develop general software systems, which must then be modified, using business-domain capabilities, to fit an idiosyncratic business environment to create value for the customer. This, in turn, earns profits for the focal firm. Both these capabilities are essential for successfully providing services to customers and, therefore, have rent-generation potential. While technological capabilities can be utilized in multiple industries, business-domain capabilities can be applied to different firms within the same industry; therefore both these capabilities are general and not firm-specific. We now focus our attention on how these capabilities developed through learning impact performance.

Internal capability development through learning

Learning is a powerful way to acquire intelligence. Many organizations have invested time and resources to develop capabilities through learning, and the ability to learn is considered to be a unique source of sustainable competitive advantage (Lane, Salk, and Lyles, 2001; McEvily and Marcus, 2005; Senge, 1990; Zollo and Singh, 2004; Zollo and Winter, 2002). Strategy scholars have suggested that performance differences across firms may be attributable to knowledge asymmetries and differences in the ability to learn, which in turn offers firms competitive advantages (Barabba and Zaltman, 1991; Conner and Prahalad, 1996; McGill and Slocum, 1994; Nonaka, 1994; Senge, 1990). Levinthal and March (1993) examined learning processes as instruments of organizational intelligence. Learning behaviors that may enable a long-term adaptive capability are known as strategic learning (Kuwada, 1998). Organizations that are able to convert information into knowledge and wisdom tend to be more successful (Davis and Botkin, 1994), especially in high-velocity environments (Eisenhardt and Martin, 2000; Volberda, 1996). It follows that if an organization can use proper mechanisms and adequate incentives to create an internal environment of continuous learning, it can realize performance advantages over competitors. This study examines the performance implications of capability development through two types of learning mechanisms: informal learning on the job and formal learning through training and evaluation.

Informal learning: experience

Firms develop capabilities through trial and error and learning by doing (Nelson and Winter, 1982).

[4] Business-domain capabilities are fungible within the same industry sector, since industry knowledge is transferable among firms within the same industry. For example, a software engineer who has a year's worth of experience working for Citibank on a banking software development project may be reassigned to another project developing similar software for Bank of America. The software engineer will be able to use his knowledge and experience from having worked on the Citibank project to his benefit in the subsequent project for Bank of America

Research on acquisitions and internationalization supports the view that as firms gain experience, they become more proficient at deploying knowledge resources and capabilities (Haleblian and Finkelstein, 1999; Zahra, Ireland, and Hitt, 2000). Previously acquired knowledge allows experienced employees to make decisions intuitively and process information more quickly, thereby improving performance (Chase and Simon, 1973). Informal learning happens over time through various processes, such as learning by doing, learning from teammates' tacit knowledge sharing, learning by trial and error while working on projects, and on-the-job mentoring by senior colleagues (Haas, 2006). Employees can acquire business-domain capabilities through repeated interactions with customers, which often involve several projects over an extended period of time (Ethiraj *et al.*, 2005; Kang and Hahn, 2009). Repeat client interaction enhances the relationship, helps build business-domain-specific absorptive capacity (Cohen and Levinthal, 1990; Dyer and Singh, 1998) and enables employees to offer customers higher value-added services. It can thus be reasonably expected that

Hypothesis 1: *Business-domain capabilities developed through experiential learning are positively related to firm performance.*

Extending the same logic to technological capabilities, it is clear that by repeatedly working on a certain technology, employees develop expertise and increase their efficiency. Greater experience with a technology is also associated with reduced errors, hence less reworking. It also enables employees to develop superior output that lasts longer and requires less maintenance. This should translate into better quality, which leads to higher performance. Therefore, it may be predicted that

Hypothesis 2: Technological capabilities developed through experiential learning are positively related to firm performance.

Formal learning: training

Although a substantial body of literature on training and development exists, most of it focuses on individual learning and transfer (Kozlowski *et al.*, 2000) and overlooks training and evaluation as mechanisms of capability development. Following Pisano (1994, 1996), formal learning is similar to learning before doing, which teaches the cause-and-effect relationships underlying a problem and imparts theoretical knowledge. Formal education enhances one's ability to receive, decode, and assimilate information (Nelson and Phelps, 1966), which in turn leads to better decision making (Griliches, 2000). It is well documented in the strategy literature that experience accumulation, knowledge articulation, and highly deliberate investment in learning mechanisms such as knowledge codification (Zollo and Singh, 2004) play a powerful role in the evolution of dynamic and operational routines (Zollo and Winter, 2002). Business-domain capabilities involve a deep understanding of the customer's industrial environment, business requirements, and preferences, which enable firms to tailor a given technology or service to meet the needs of their customers (Ethiraj *et al.*, 2005). Such knowledge may be gained through specialized training programs and courses designed for a certain business domain—for example, banking, telecom, or retail. Bapna *et al.* (2013) show that business-domain training improves employee performance, while Kang and Hahn (2009) argue that business-domain knowledge enhances project performance. Certification exams facilitate absorption and internalization of the knowledge gained through training. A deep knowledge of a customer's industry enables firms to provide value-added services that can improve the firm's performance. Therefore, it can be predicted that

Hypothesis 3: Business-domain capabilities developed through formal training and evaluation are positively related to firm performance.

Formal training programs in different technological disciplines are also useful for imparting relevant knowledge to employees. A variety of institutes offer specialized courses in various technologies to prepare trainees for live projects on the job. With the rapid advancement of technologies, it has become essential for technical employees to retool themselves regularly to avoid skills obsolescence and meet specific job requirements (Bapna *et al.*, 2013; Pazy, 1996). Such retooling is often accomplished through specialized training and certification courses aimed at upgrading technical skills and

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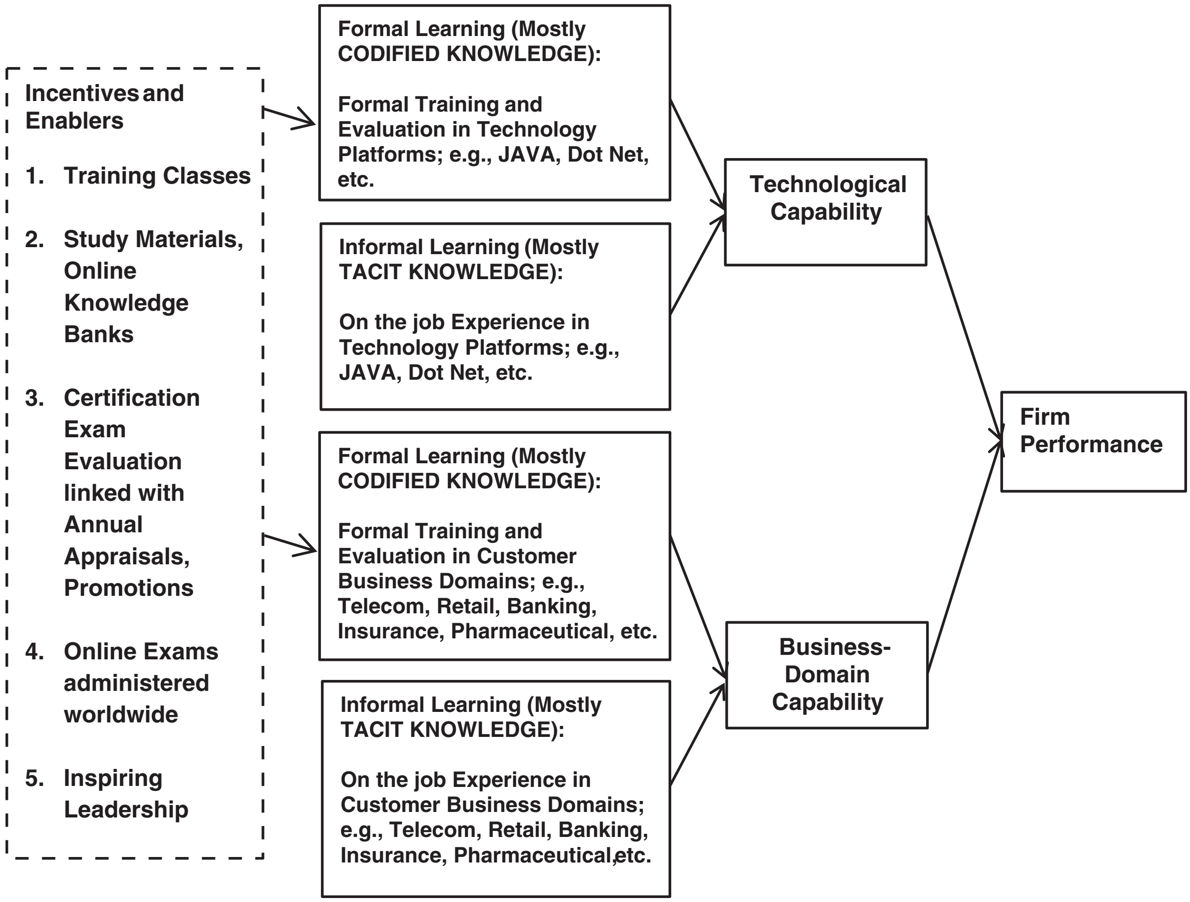

Figure 1. Pictorial representation of capability development mechanism[5]

enhancing performance. Therefore, it is reasonable to expect that

Hypothesis 4: Technological capabilities developed through formal training and evaluations are positively related to firm performance.

It is likely that these two mechanisms will have pros and cons, as well as differential impact on capability development. For example, employees generally complete formal training in a couple of months, after which time they start working on client projects. On-the-job learning, by contrast, often takes several years. Training also tends to be labor intensive and expensive (Salas and Cannon-Bowers, 2001), especially if employees are trained during work hours. On-the-job learning is less expensive, since employees pick up skills through repeated trial-and-error as they work. Core rigidities and competency traps may also reduce the value of technical experiential learning (Leonard-Barton, 1992; Levitt and March, 1988). The above flowchart in Figure 1 shows how the tacit and explicit knowledge that individuals gain using informal and formal learning modes leads them to develop different capabilities, which ultimately improve firm performance.

The two methods of learning (experiential and formal training and evaluation) enable employees to upgrade their knowledge and skills in different software technologies as well as industry business-domains. With this enhanced knowledge capital project teams are able to perform better in all aspects of project execution (e.g. requirements analysis, scoping, design, coding, testing, etc.). Over time, these learning mechanisms impart

[5] Firm performance is an aggregation of project performance in this context since the focal firm delivers customized software to clients by executing multiple projects year after year

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the project team with the superior ability to execute projects efficiently (fewer errors, less rework, within schedule and effort estimates), and deliver high value-added solutions to clients. This in turn leads to greater profitability.

EMPIRICAL SETTING AND CONTEXT

The empirical setting is based on a field study conducted over three months during 2009 and 2010. The study included multiple visits to the headquarters of a large multinational software services firm located in Bangalore, India. In the spirit of Bartel, Ichniowski, and Shaw (2004), this is a single-firm study that uses detailed quantitative data to examine the key production processes by first identifying the production units (e.g., teams of employees) and then conducting econometric hypothesis testing to determine organization-specific determinants of performance.[6] The software-services industry is particularly conducive to testing this type of theory because it is a high-technology, knowledge-based industry in which the chief resource is the large number of talented and skilled software engineers who account for more than 70 percent of the cost of producing the service.[7]

This particular firm provides customized software solutions for various clients in such industries as banking, insurance, telecom, retail, transportation, manufacturing, and pharmaceuticals. To provide superior solutions, firms need a thorough knowledge of the various general software technology platforms (Java, Dot Net, Mainframe, etc.), as well as a deep knowledge of the client's industry and business imperatives. The subject Indian firm was faced with competitive challenges from foreign multinationals (e.g., Accenture, IBM, HP, Cap Gemini, and others) that had decades of experience (and superior industry-domain-specific capabilities) in providing customized IT services to clients across multiple industries. Foreign firms were able to mimic some of the comparative cost advantages of the focal firm by setting up global software-development centers in India and recruiting fresh graduates from Indian engineering schools at a fraction of the salary of their U.S.-based counterparts. Faced with such a competitive threat in its home country, the firm decided to upgrade its capabilities, especially in the delivery of high-end services tailored to clients' business requirements. With the goal of bridging the capability gap between itself and established foreign multinationals, the firm made huge investments in specialized training for its software engineers in different technology platforms and industry domains and then developed certification exams to evaluate their learning and knowledge absorption.

The firm initially rolled out the exams to senior employees (project managers and service delivery heads); over time, it included employees at lower levels. The idea behind this top-down approach was that if senior executives could buy into the new scheme, then midlevel managers would accept it and follow through. At the outset, there was internal resistance and some controversy regarding whether the certification exams would enhance employee competency. In the end, however, most senior executives stood behind the initiative and implemented it. The firm initially offered certification exams in various platforms such as Java, Dot Net, C++, Mainframe, and so forth, and then gradually introduced certifications in newer technologies. In 2006–2007, the firm introduced domain-specific certification exams to augment the industry-domain knowledge of employees working with customers in different industry verticals (banking, healthcare, retail, etc.). Appendix S1, Supporting Information presents a few examples of certification exams. The firm required every employee to take at least two exams every year, out of which one had to be in a technology related to his or her project work. After seeking approval from a supervisor, an employee could then choose to take the second exam in either a business domain or a technology. Special training materials and programs were available at the library and training centers, as well as in online knowledge repositories. Certification was mandatory for all employees working on client projects at all locations in India and worldwide. Appendix S2, Supporting Information presents a brief history of the certification initiative based on interviews with top management.

Software services are normally rendered to clients through individual projects; therefore, the

[6] Ichniowski and Shaw (2003) used the term *insider econometrics* to describe single-firm studies that use a large sample of internal project-level data based on extensive fieldwork

[7] The focal firm confirmed this 70 percent figure for their cost of operations. Interviews and discussions with industry professionals from multiple firms confirmed this rough figure for other Indian IT services firms. Earlier estimates by Lakha (1994) suggest that labor costs accounted for about 70 percent of all software costs in the early 1990s

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hypotheses were tested using detailed operational, financial, and human capital data at the project level from a large sample of software-development projects. Since capabilities in this industry primarily exist in and revolve around software projects within firms, a software project was chosen as the appropriate level of analysis (Ethiraj *et al.*, 2005). Since each project execution involves a combination of different routines, our assumption is consistent with previous theory, which defines capabilities as high-level routines or collection of routines (Winter, 2003). In a similar empirical setting, Ethiraj *et al.* (2005) demonstrated the positive performance impact of project-management capabilities, while Huckman *et al.* (2009) established the importance of team familiarity in high-performing projects. More recently, Bapna *et al.* (2013) studied the impact of employer-provided training on employee performance in the IT services industry. Since the firm delivers service to customers by executing multiple projects for different customers, it may be assumed that firm performance is an aggregation of project performance (Ethiraj *et al.*, 2005). Therefore, firm-level inferences may be drawn from analyzing a large sample of projects executed by a single, large, globally renowned company.

METHODS AND DATA

At the outset, we conducted a series of unstructured interviews with employees at different levels over multiple visits to understand the software development process, success factors, and capability-development initiatives undertaken by a leading software-services provider headquartered in India. Following Banerjee and Duflo (2000), we collected detailed quantitative data at the project level. More than 95 percent of the firm's revenues are generated from the export of customized software to foreign countries; 60 percent of which come from North America. The dataset included information on revenues, gross margin, human-resource factor inputs, capability measures, and various project characteristics—such as customer industry domain, team size, duration, and technological platform—all recorded at the project level. The data consist of 465 software development projects completed by the firm over a three-year period between April 2005 and March 2008. After dropping projects with missing data, the sample was reduced to 427 projects.[8] After the introduction of independent variables, sample size fell to 347 projects. Software development projects often involve schedule and cost overruns, because they are often plagued with complexities and uncertainties due to rapidly changing technologies and client requirements. We collected information on these operational metrics at the project level.

The software-development project-level data consist of objective performance measures and controls that allow a comparison across projects. In addition to the project-level operational and financial data, we collected human capital information on 5,536 employees who were working on these projects. We also collected data on the 21,502 certification examinations these employees had taken. Of these, 11,932 were technological exams, and 9,570 tested business-domain knowledge. Using exam scores, aggregate team-level competence measures were developed for each project team based on the two capabilities under consideration. The unit of analysis was a software development project executed for a given customer, and all variables were measured at the project level to allow for proper estimation of the performance impact of both the technological and business-domain capabilities. Since the firm has a single output—customized software using skilled manpower—project performance was regressed against the different capability variables, controlling for certain project-specific factors. These are discussed below.

Measures

Dependent variable

The dependent variable was project gross profit (revenues minus direct costs). Direct costs include the salaries of project team members, related travel costs, and software licenses required for a given project. Again, project costs were based mostly on skilled labor.[9] All revenue numbers are given in USD equivalents adjusted for currency fluctuations and recognized as of the day of

[8] Projects with missing data did not vary substantially on the main variables compared with projects that had no missing data

[9] The salaries of software engineers accounted for more than 70 percent of project costs, and the remaining costs were associated with project-related travel, communication with onsite customers, and software and hardware

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project delivery—that is, the project's end date. Project-level gross profit is an important outcome variable for a study of firm capabilities, because these capabilities primarily exist around projects and are developed through repeated project execution for multiple customers over time. Firm profits may be assumed to be an aggregate of project profits (Ethiraj *et al.*, 2005), since the firm in this study essentially executes different types of projects for customers and has no other revenue-generating source. Overhead costs were not included in calculating Project Gross Profit, since they were not related to the project-level capabilities we were measuring. The dependent variable was logged; year dummies in the regression account for any changes in overhead costs due to inflation over the three-year study period.[10]

Independent variables

Technological capability was measured by the level of technological expertise of the project team in the technology of the project in which the team had been deployed. This variable was measured using team members' scores on different technological exams administered to all employees. The firm had developed several exams for each technology stream (Java, Dot Net, Mainframe, C++, etc.). The firm offered these exams at three levels of increasing difficulty (level 1, the easiest, to level 3, the most difficult). Employees were allowed to take exams at all three levels (with the approval of their supervisors) but were required to complete the lower-level exams (levels 1 and 2) before taking the higher-level exams (levels 2 and 3). Exams were administered online at a designated examination center on campus and typically lasted an hour. They comprised 50–100 multiple-choice questions totaling 100 points.

The firm provided specialized coursework and preparation material for each of these exams. Employees were required to take at least two exams a year, and the results were tied to their annual performance appraisal. This ensured that exams would be taken seriously and that employees would prepare well in advance to perform well. For each project, a technology competence score was developed by adding the exam scores of every employee who worked in the project. In calculating these project team scores, the following principle was adopted—an individual's exam score was included if the exam was in the same technology as the project technology and if the employee took the exam at least 90 days before the project completion date. Because most projects in the sample ranged in duration between three and six months, this method ensured that the employee had used the knowledge he or she gained from the exam in the project. For exams with different levels of difficulty, a simple weighted scoring method was used: we multiplied the exam score by two (for level 2 exams) or three (for level 3 exams).[11] The total team score for a project was therefore the sum of the weighted exam scores for each employee involved in the project, calculated after satisfying the above principles. The final score was then divided by the team size to arrive at a project technology competence score. This aggregation method was supported by interviews conducted with senior managers and service delivery heads at the target firm. This type of aggregation, achieved by calculating the mean team score, follows theoretical expositions on multilevel constructs by Chan (1998) and Klein and Kozlowski (2000). A higher score on technology competence indicates greater technological expertise for the project team. Ideally, this should translate into greater productivity and higher gross profits. The expected sign on this variable is positive.

A second measure of technological capability was developed by aggregating the experience of all project team members in the particular technology of the project. For example, if a project used Java technology, the total experience of all team members in previous Java projects was added and averaged by team size to arrive at a technological experience measure in months. Project teams with more technological experience are expected to develop better-quality software that meets all

[10] A normal distribution has skewness zero and kurtosis 3. The skewness and kurtosis of the outcome variable (log of gross profit) were 0.039 and 3.237, respectively, suggesting that the distribution of the dependent variable was nearly normal, which supports the use of OLS regression models. Log transformation of "Gross Profit" improved model fitness

[11] This type of weighted aggregation is commonly used in studies assessing the effectiveness of training and examinations. We do not expect the use of arbitrary weights (1–3) for different exam levels to create major measurement issues, because employees were allowed to take exams at higher levels (2 and 3) only after passing lower-level exams (1 and 2). Therefore, team scores consisting of higher-level exams include the scores of the lower-level exams taken by the same employee.

technical requirements and satisfies all functional goals of the client. Such projects should also show higher efficiency and productivity, which provide higher profits. The expected sign for this variable is positive.

Business-domain capability was measured by the level of client industry knowledge of the project team. A good understanding of a customer's industry allows a project team to develop higher quality software that meets the customer's business requirements. This expertise is different from pure technical expertise. Knowledge of a customer's business domain enables a team to appreciate the customer's business priorities. This knowledge helps the team translate a customer's business requirements into technological specifications to develop into a suitable product or service using various combinations of software and hardware. The firm developed several exams in different industry domains at three levels of increasing difficulty, similar to the technical exams. Following the same principles as the technological exams, a composite domain-competence score was calculated for each project by adding all the weighted scores (by exam level) for each project team member and then normalizing those with the team size. Project teams with higher domain-competence scores should perform better as they are expected to develop software applications aligned with customers' business environment, which will translate into higher productivity and greater project gross profits. The expected sign for this variable is positive.

A second measure of business-domain capability was developed by aggregating the experience of all project team members in the particular industry domain of the project client. For example, if a project was in the banking domain, then the total experience of all team members in previous banking projects was added and divided by team size to arrive at the *domain experience* measure, also in months. Project teams with more business-domain experience are expected to develop better-quality software that satisfies all the business goals of the client. Such projects should be more efficient and productive, which leads to greater profits. The expected sign for this variable is positive.

Overall, the four capability measures we employed measure the knowledge capital of a team; and since capabilities reflect the deployment of resources (Makadok, 2001), we expect that capability differences across projects within the same firm will reflect the productivity and performance differences among them. Hence, an increase in a project team's knowledge capital generally accompanies increased productivity of knowledge resources (in this case, human capital) and performance over time.

Control variables

Following past studies (Ethiraj *et al.*, 2005; Huckman *et al.*, 2009), a number of controls were used for different factors that might affect project gross profit, such as team size, total effort (person-hours), project duration (days), onsite-offshore effort ratio (onsite effort/offshore effort), customer industry domain, development platform technology, year, and contract type (see Appendix S3, Supporting Information for detailed description of all control variables). Following the results of Ethiraj *et al.* (2005), we also controlled for three significant independent variables used to measure project management capabilities: schedule slippage (Actual Duration minus Estimated Duration divided by Estimated Duration), critical in-process defects (number of critical defects encountered during project life), and effort deviation (Actual Effort minus Estimated Effort divided by Estimated Effort). This was done to show the importance of capabilities over and above what past studies have found. The models were estimated using fixed effects specification (Greene, 1997); since the customized software services output varies with domains and technologies, it was essential to control for domain-specific effects by including dummies to represent client industries.[12] The regression analysis shows that variability in project profitability across projects is explained by variations in the levels of the independent variables (e.g., the four capability measures) after controlling for various project-specific controls.

[12] The target firm did not make client names available due to nondisclosure agreements, so we used client industries to control for domain-specific effects. Based on multiple interviews with project managers at the client site, it was clear that a major portion of business-domain knowledge was specific to the industry and, therefore employees working for a particular client (say, Citibank) in the banking domain could easily move on to another client's (say, Bank of America) project within the same domain due to broad similarities in business processes and systems. This was also the reason why the target firm developed domain-specific exams instead of developing client-specific exams to upgrade its employees' capabilities

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RESULTS

Table 1 presents the descriptive statistics and correlation matrix of the key variables used in this study. Table 2 presents the coefficient estimates from the fixed effects regression analysis. The second column lists the predicted signs of the key independent variables used in the model.

The column labeled Model 1 presents the base results with only the control variables in the model. We used an additional control (No critical defects) to distinguish between the many projects that had no critical in-process defects and those with at least one critical in-process defect. This variable was used only in Model 1, to validate previous results obtained by Ethiraj *et al.* (2005).[13] In Model 2, the domain experience variable was introduced and, as expected, the sign is positive. In Model 3, the technology experience was included to check for its impact on performance, but it turned out to be insignificant. Thus Hypothesis 1 was supported and Hypothesis 2 was not.

Model 4 shows both the independent variables for business-domain capability as the domain competence score is included to check its impact on project performance. Following econometric methods similar to those adopted by Himmelberg, Hubbard, and Palia (1999: 364), we used an additional control (zero domain competence score) to distinguish some projects for which domain scores were not available, to account for any biases that may have arisen due to systematic differences between projects with and without domain scores. As expected, the domain competence score was positive and highly significant. Finally, the technological competence score was added in Model 5. Although the sign is positive as expected, it has no significant impact on project performance. Using the full model (Model 5, Table 2) to interpret the results, we find support for Hypotheses 1 and 3, while Hypotheses 2 and 4 are not supported. Overall results show that business-domain capability has a positive impact on project performance, but technological capability does not have any significant positive effect on project performance.

[13] The signs on all three independent variables used by Ethiraj *et al.* (2005)—schedule slippage, in-process defects, and effort overrun—are negative and significant, which validates their results

Table 1. Descriptive statistics and correlation chart of variables (N = 347)

Variables	Mean	STDEV	1	2	3	4	5	6	7	8	9	10	11	12
1 Log (gross profit)	5.1112	0.977	1											
2 Domain experience	43.44	30.31	0.122*	1										
3 Technology experience	27.15	18.88	−0.021	0.314*	1									
4 Domain competence score	15.38	44.06	0.091	0.293*	0.064	1								
5 Technology competence score	16.4	52.93	0.031	0.163*	0.088	0.695*	1							
6 Effort deviation	0.0287	0.1368	−0.022	0.019	−0.079	−0.208*	−0.152*	1						
7 Schedule slippage	0.0681	0.2253	0.024	0.024	0.018	−0.051	−0.067	0.232*	1					
8 Critical in-process defects	0.0224	0.0481	0.017	−0.044	0.064	0.064	0.061	0.007	−0.028	1				
9 Log (team size)	2.3124	0.6888	0.779*	−0.017	−0.185*	−0.046	−0.095	0.248*	0.085	0.034	1			
10 Log (effort)	8.8724	1.0103	0.86*	0.122*	−0.071	−0.017	−0.036	0.243*	0.116*	0.031	0.862*	1		
11 Log (project duration)	5.3579	0.5283	0.639*	0.229*	0.045	0.033	−0.026	0.112*	0.243*	0.006	0.486*	0.701*	1	
12 Onsite/offshore ratio	0.3065	1.024	−0.007	0.098	0.01	−0.01	−0.041	−0.009	0.002	−0.019	0.106*	0.032	−0.05	1

*Indicates pairwise correlations significant at 0.05 level or lower.

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Table 2. Regression estimates

		Dependent variable: log (gross profit)				
Independent variables	Predicted sign	Model 1	Model 2	Model 3	Model 4	Model 5
Domain experience	+		0.0025***	0.0026***	0.0020**	0.0021**
			(0.0009)	(0.0010)	(0.0009)	(0.0009)
Technology experience	+			−0.0005	−0.0005	−0.0007
				(0.0016)	(0.0016)	(0.0015)
Domain competence score	+				0.0027***	0.0024**
					(0.0009)	(0.0011)
Technology competence score	+					0.0004
						(0.0007)
Controls						
Effort deviation	−	−1.356****	−1.6651****	−1.6663****	−1.6857****	−1.6898****
		(0.3907)	(0.4321)	(0.4325)	(0.4396)	(0.4412)
Schedule slippage	−	−0.2623**	−0.1992*	−0.1989**	−0.1762	−0.1784
		(0.1232)	(0.1185)	(0.1187)	(0.1184)	(0.1194)
Critical in-process defects	−	−0.9688**	−0.5716	−0.5600	−0.5827	−0.5767
		(0.3820)	(0.4115)	(0.4161)	(0.4023)	(0.4021)
Team size[a]		0.3111****	0.3613****	0.3559****	0.3910****	0.3952****
		(0.0683)	(0.0768)	(0.0810)	(0.0857)	(0.0868)
Actual effort[a](person hours)		0.6441****	0.6430****	0.6459****	0.6278****	0.6251****
		(0.0604)	(0.0658)	(0.0674)	(0.0691)	(0.0697)
Actual project duration[a](days)		0.2704****	0.1708**	0.1705	0.1488*	0.1496*
		(0.0721)	(0.0782)	(0.0783)	(0.0782)	(0.0782)
Onsite/offshore ratio		−0.0475****	−0.0609****	−0.0610****	−0.0661****	−0.0660****
		(0.0093)	(0.0119)	(0.0118)	(0.0129)	(0.0130)
Industry domain		Sig	Sig	Sig	Sig	Sig
Technology platform		Sig	Sig	Sig	Sig	Sig
Year		Sig	Sig	Sig	Sig	Sig
Contract type		Sig	Sig	Sig	Sig	Sig
No critical defects		Sig	−	−	−	−
Zero domain score		−	−	−	Sig	Sig
Constant		−2.8970****	−2.5808****	−2.5911****	−2.6069****	−2.5826****
		(0.3568)	(0.4177)	(0.4260)	(0.4103)	(0.4172)
R^2		0.8284	0.8349	0.8350	0.8384	0.8385
N[b]		427	347	347	347	347

[a] Variables are logged.
[b] All the models were re-run using the final sample of 347 projects and the results were unchanged in sign and significance.
****$p < 0.001$; ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.
Heteroskedasticity robust standard errors reported in parentheses.

Robustness tests

To verify the costs associated with the certification initiative, we approached the head of the Education and Research Division that was responsible for administering the exams. We learned that, on average, the firm invested 10 million USD per year on its training and certification infrastructure and that these expenses were part of the firm-wide overhead. The firm posted annual revenues of more than 8 billion USD in 2014 and has posted average after-tax profits of more than 25 percent per year over the past decade. Therefore, these expenses for the certification initiative should not have any significant impact on profitability and should not make any difference in the interpretation of our results.

To check whether aggregation methods for certification exam scores might affect project performance, we conducted the same tests using the standard deviation for the entire team's exam scores, the standard deviation of the mean score of all team members, the median, and the highest score obtained by any team member. We did this to check for any performance effects of the dispersion of individual scores in a team and to check whether the median score or the highest-performing member in a team could predict

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team performance regardless of the capabilities of other members. In all models, these different scores were insignificant, except for the standard deviation of the technology competence scores, which had a marginally significant negative impact (at the 10% level) on project performance. To check for possible effects of dispersion of employee experiences within a project team, we conducted similar tests for the employee experience variable by calculating the median, maximum, standard deviation, and variance of employee experiences in both technologies and business domains. In all models, the different measures of team experiences were insignificant. These results are consistent with the results in Model 5 (Table 2), suggesting that the identified effects are robust for alternative explanations. We also tested for possible interaction effects between the four independent variables, as well as between the independent variables and controls. In order to check if the complexity of the task or project had any moderating effect on the impact of capabilities on project performance, we tried various interactions of the four capability measures and project size (function points[14]). Since these tests did not produce any significant results, we report only the results of main effects.

As a robustness measure, we tested for client repeat project influences on the results in three ways.[15] First, we clustered standard errors with respect to client IDs (Model 1, Table 3 in Appendix S4, Supporting Information), and the results were unchanged. We also included two separate control variables in the final model (Model 5, Table 2): (1) the number of concurrent projects executed by the firm for the same client in a given year (see Model 2, Table 3 in Appendix S4, Supporting Information), and (2) the number of past projects executed for the same client in previous years (see Model 3, Table 3 in Appendix S4, Supporting Information). Our principal inferences based on the final model (Model 5, Table 2) were invariant to these additions. The results are presented in Models 2 (concurrent projects with same client in a year) and Model 3 (past projects with same client in previous years) of Table 3 (Appendix S4, Supporting Information), respectively. Interestingly, while controlling for repeat client projects, we found no effect for projects that were executed with the same client in the past. However, the control for the number of concurrent projects associated with the same client in a given year was significantly and positively correlated with project performance. One reason for this anomaly could be that project teams are dissolved after project completion and team members move on to new projects with different clients; so much of the client-specific knowledge learned during project execution is lost. Repeat projects from the same client in later years cannot capture this knowledge, because a new team is created to deliver the repeat project. If, however, several projects are executed for the same client simultaneously, this loss of client-specific knowledge is reduced, since the teams can easily interact, exchange information, and resolve project-related problems. This also has the potential to reduce managerial overheads and improves economies of learning associated with the same client. During multiple visits to the firm headquarters, we learned that all projects conducted for a particular client are housed in the same physical space (floor or building) to enable information sharing across projects and to improve learning efficiencies. We believe this is one of the reasons why repeat projects conducted in later years do not show any performance impact, while multiple projects executed simultaneously with the same client show a significant positive impact on performance.

Evaluating selection bias

Selection can be a concern in our empirical setting if the most competent employees are systematically staffed in projects which then turn out to be highly profitable. This might happen if, in conjunction with HR staff, a project manager identifies those employees scoring high on certification exams and selects a team composed of the top scorers, and/or selects a team of employees with very high experience. In such situations, any performance benefits resulting from a certification-exam initiative or on-the-job learning may be due not to formal or informal learning, but rather to selecting the smartest or most experienced employees and excluding employees with low scores or little experience.

To evaluate these issues, it is important to examine how software development projects are staffed. Detailed interviews with executives at the focal firm

[14] Project size was measured in function points, which gives us a measure of the amount of software code that was developed adjusting for complexity. See Appendix S3, Supporting Information for detailed explanation

[15] We would like to thank one anonymous reviewer for suggesting these three tests that have made our results stronger

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revealed that the first step in staffing a new project is an estimation of project size and complexity (function points), effort (person-hours), and schedule (duration). The software industry is very competitive: major multinationals such as IBM, Accenture, HP, TCS, Infosys, Wipro, HCL, and Cognizant compete for customer projects. Such firms do not have much latitude in terms of estimates, since any slack may lead to losing a project. At the focal firm, a project manager is assigned to a project after a customer agrees to the effort and schedule estimates; these provide detailed guidelines of the types of people needed to work on the project (e.g., "a Dot Net programmer with five years' experience"). The project manager does not select specific employees for projects. Instead, a staffing group recommends software engineers based on the required skills and experience detailed in the initial estimates guideline. Generally, employees are engaged in one project at a time, and after the project is complete, team members are released to work on new opportunities that are available at that time. A project manager cannot hold onto the best software engineers indefinitely after completion of a project, especially given the constrained supply of software engineers in recent years and the high utilization rate of engineers needed to meet margin requirements. If a software engineer is engaged for a client project, he or she becomes a billable resource that earns money for the firm, but even when benched, the firm must still pay the engineer's salary. During interviews, senior executives and project managers at the focal firm mentioned that they did not have access to the certification exam scores because the exam was administered by a separate division (Education and Research) and employee scores were confidential. The managers categorically denied the idea of choosing project teams based on employees' certification exam scores. Perhaps more important is that the employee utilization rate at the focal firm was above 85 percent, which means that at any time only 15 percent of employees were available to staff new projects. Project managers had only limited ability to select the smartest engineers for their project team, since they were not allowed to select employees who were already engaged in ongoing projects.

To check whether managers use certification examination performance or employee experience as a criterion for staffing projects, we conducted tests to see whether any exam scores or experience measures were significantly related to a project's original size (function point measure[16]), schedule, and effort estimates. These three variables are usually based on managers' assessments of a project's complexity at the time the firm receives the contract and can be considered proxies of project complexity. Over the duration of a project, the actual schedule and amount of effort can change, causing overruns and slippages, which are costly for the firm (evidenced by the negative impact on project performance shown in Model 1, Table 2). A significant relationship could mean that staffing executives anticipated that the project would be complex and therefore created a team composed of those employees who had performed best on the certification exams as well as those with the most experience. It could also mean that the estimates were based on the team's capability as judged from their performance on the certification exams and their experience with different technologies and business domains.

Table 4 (Appendix S5, Supporting Information) presents the regression results using the original size (function points), effort, and schedule estimates as predictors and the two competency scores (technological and domain) and experience variables (technological and domain) as outcome variables. We ran four separate models for the four outcome variables. All models were a good fit, but none of the predictors had any significant impact on the outcome variables, which rules out the possibility that the project team was staffed based on the project's complexity. To account for unobserved ability of project team members, we reran the final Model 5 (in Table 2), including project costs as an additional control. The results were unchanged (see Model 4, Table 3 of Appendix S4, Supporting Information). In the high-tech IT services industry, project costs consist primarily (more than 70%) of employee (project team members) salaries. Salaries were also correlated with employees' unobserved ability (since the firm is highly meritocratic). Therefore, the project's cost control may be considered an effective control for the omitted variable. This would have an impact on both the outcome (gross profit) and the four independent variables (Domain and Technology Experience, and Domain and Technology Competence Scores). While this result does not conclusively prove a fully random assignment of employees in staffing projects, it

[16] Appendix S3, Supporting Information explains the function point measure, which is a proxy for project size adjusted for complexity

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gives us confidence that selection in and of itself was not the main driver for the results reported in this paper.

DISCUSSION

In this paper, we investigated how firm performance is affected by capabilities developed through deliberate investments in human assets to upgrade employees' general knowledge and skills through different types of learning mechanisms. We argued that capabilities develop over time through various path-dependent processes, such as learning by doing and deliberate sustained investments of capital and resources. We identified two different capabilities that are critical for success in the global IT services industry: business-domain capability and technological capability. The focal firm made deliberate investments in general human capital with the strategic intent of developing these capabilities and competing successfully with established foreign rivals. These investments bore fruit. The results suggest that firms can develop these capabilities through formal methods, such as specialized training and evaluation, or informal methods, such as experiential learning.

We developed four hypotheses to reflect the interplay of these different methods of developing capabilities. The results supported the two hypotheses that addressed business-domain capability. One unit of increase in business-domain competence score resulted in a 0.24 percent[17] increase in project profits. The same investment aimed at developing technological capability, however, did not yield dividends. Such certifications did enhance the technical knowledge of employees, but this knowledge did not translate into superior performance in developing better software applications. One explanation may be that technological knowledge is more codifiable: once employees learn technical knowledge during their initial training after joining the firm, they can apply it on the job to enhance project performance. Over time, extra training and certifications may not add much to employees' technological expertise. After discussions with employees at the focal firm, it became apparent that the technology certifications were at such a high level that the knowledge they certified was not readily usable for client projects. The managers justified these certifications by saying that this knowledge would be useful in the future (Chatterjee, 2011). Domain knowledge, on the other hand, is more subjective and tacit and thus relatively difficult to codify. However, certain aspects of domain knowledge can be codified in the form of training manuals and certification exams. These codifications of domain knowledge create value because employees can use them in actual project work in a relatively straightforward manner.

Similarly, business-domain expertise accumulated over several years of project execution experience in the client's industry appears to be more valuable than technological experience. A one-unit increase in business-domain experience resulted in a 0.21 percent[18] increase in project profits. Employees with higher levels of business-domain experience adequately compensate for their increased salary by making superior contributions to project performance. Therefore, we find that while investment in business-domain capabilities (through focused coursework and certification evaluation examinations) created value; investment in technological capabilities did not result in similar payoff. After discussing this with senior managers at the focal firm, it became clear that with increased technological experience, roles and responsibilities become more complex. Employees with greater experience take on responsibilities for project- and client-expectations management, which leads to increased performance challenges. Even though project managers have significant technological experience, they do not get involved in developing software. Therefore the lack of significance of our technological experience variable could also be attributed to obsolescence (Pazy, 1996; Thompson, 2007).

The results suggest that technological skills are a necessary but not sufficient condition for earning higher profits. Without technological capabilities, firms will not be able to execute software services projects; however they must possess business-domain capabilities in order to customize the technology to meet the integral requirements of their clients and provide higher value. Customers

[17] For an average project, this suggests an approximate increase of $648 in gross profits per one-point increase in average team business-domain competence score. The average project profit in our sample was $269,948.1

[18] On an average project, this translates to about $567 increase in gross profits per one-month increase in average team business-domain experience

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are willing to pay premium for business-domain skills as these skills enable the focal firm to tailor a general technology to the client's internal business environment and deliver value. Therefore leveraging the general technological skills in combination with the business-domain skills enables the focal firm to earn superior returns.

Previous research has mainly focused on experiential learning as a means of developing capabilities. Bapna *et al.* (2013), Ethiraj *et al.* (2005), Huckman *et al.* (2009), and Kang and Hahn (2009) are some recent studies that have examined the nature and impact of capabilities in the IT services context. Our paper advances empirical research on capabilities by showing the impact of formal and informal learning on project performance and, by extension, firm performance. Bapna *et al.* (2013) used a similar setting to assess the impact of different kinds of training (business domain, technical, general, firm specific) on individual employee performance. This paper has taken the logical next step: assessing the impact of employee learning on project team and firm performance. While Bapna *et al.* (2013) showed that general training in technology and business domain improved individual performance, we provide empirical evidence that such general training and certifications also improve project-level and firm performance. This is an important finding: individual employee performance may not always correlate with overall firm performance, but in this context, it does.

Ethiraj *et al.* (2005) used a similar setting and project-level data to show the impact of client-specific and project-management capabilities on project performance. However, they used operational metrics such as schedule slippage, effort overruns, and in-process defects to measure capabilities and overlooked the importance of human capital variables, which are at the core of capability development in the knowledge-intensive IT services industry. We have used human capital variables in the form of employee work experience and certification examination scores to develop our capability measures and assess the impact of formal and informal learning on project profitability.

Finally, we also found some evidence for capability evolution over time as a result of deliberate investments in acquiring technological and domain-specific competence. The certification examinations came into effect after the first year of the study (2006); thereafter, their impact was noticeable in project performance over the next two years (2007–2008). Average gross contribution from projects increased from 65.9 percent in the first year to 69.3 percent in the latter two years. Thus, investments in capability development resulted in positive performance effects at the project level. Tighter control over interim project milestones, with better schedule estimation and management, reduced the average schedule slippage of projects by 64 percent in 2007 and 2008 compared with 2006. This emphasizes the value of improving schedule estimations and sticking to them.

This study of firm capabilities brings forward several important issues in business strategy. First, we found that the firm realized positive returns to its general human capital investments, at least in the short run. Since this firm has been and continues to be highly profitable (average annual profitability after tax has been more than 25% for the past decade), this study justifies human capital investments in the form of general training and certification exams, even though it may be valuable to competitors. In knowledge-based industries such as IT services, capability upgrade through continuous learning is the only way to maintain competitive parity, due to the rapid change in technologies and customers' business requirements. In fact, one of the founders of the firm commented,

> *"A knowledge company can only prosper by investing in its employees."*

In response to my queries about the possibility that rivals could poach certified talent, the vice president of human resources expressed this view:

> *"I tell employees who plan to quit after taking a few certifications, 'These certifications offered by our company are like stock options that continuously enhance your skills and, hence, your market value. The decision to cash out by quitting and joining another firm for higher pay is entirely up to you. But you should bear in mind that the competitor firms are unlikely to make the same investments in building your skills, so, once you leave us, you may no longer have the same opportunity to build your future competencies and earning potential.'"*

We also asked the CEO for his views on attrition. He responded,

> *If certain employees choose to quit after taking a series of certification exams, I consider it as a contribution to the IT industry that would also enhance our brand among peers and customers.*

These comments from top management reflect the firm's view on investments in general skill building and suggest that they consider general skill building to be a strategic imperative. Therefore the fallout of attrition was a problem that they would have to accept and try to minimize by keeping employees motivated and happy by designing superior compensation packages. This is consistent with Campbell *et al.* (2012) and complements their theoretical propositions.

Second, this study shows that firms can develop capabilities with strategic intent by deliberately investing in different types of learning modes (formal instruction and evaluation as well as work-based experiential learning). Technological capabilities can be applied in different industries, while business-domain capabilities, are not fungible across multiple industries. Business-domain expertise is difficult to develop because it requires long-term investments—in this case, a dedicated corporate learning infrastructure consisting of specialized training, focused study materials, online knowledge repositories, mandatory certification exams, etc. Once the firm has made such investments, however, these capabilities create superior value for the firm and provide enduring advantage over competitors simply because it is extremely difficult to replicate such an elaborate investment for continuous learning in a short timeframe without incurring huge costs. This is consistent with past research (Lee *et al.*, 1995; Weill and Aral, 2006; Zwieg *et al.*, 2006).

Finally, to address the knowledge gap identified by Ray *et al.*'s (2004) call for research attention to the selection of disaggregated dependent variables, we chose project performance as the dependent variable. Capability measurement at the aggregate firm level does not shed light on the true foundations of the capabilities nor on the mechanisms by which capability-seeking human capital investments influence performance. We believe this contributes to the empirical literature on firm capabilities by using employee-level human capital variables that are closer (compared to firm-level measures) to the actual phenomenon of capability development of individuals that aggregates up to the project and firm-level capabilities. Firm-level performance is a distant measure compared with project-level performance, which is the immediate outcome of a project team's efforts combined with its knowledge capital and capability. This gives clear direction to scholars and practitioners about the locus of capability development and how firms can improve their capabilities by making appropriate human capital investments, such as internal training and certifications.

Software development is a complex team effort. This study enhances scholarly understanding of what type of capability is important in the IT services industry and how investments in corporate learning initiatives affect project performance. Our findings thus shed light on the micro-level foundations of capabilities—an area of increasing research interest among strategy scholars. Contrary to received theory, investments in general human capital led to positive performance outcomes. Surprisingly, for a technology consulting firm, investing in pure technological expertise was not what made the difference. It was knowledge of the customer's business and the ability to use technology to solve customer's business problems that provided significant returns and created superior value for the firm.

Limitation and directions for future research

Like most studies, this one has certain limitations. Because it is a single-firm study in one particular industry that has its own economics and idiosyncrasies, generalizability to other settings is unclear. While it would have been ideal to include projects from multiple firms, it is extremely difficult to obtain such a rich set of detailed, operational, human capital data and performance metrics at the same operational level from a large number of firms. Such an endeavor was beyond the scope of our project. In terms of growth, profitability, market capitalization, and reputation, the firm we studied is among the top five in Indian IT services and is a leading global IT services provider. The worldwide IT services industry accounted for 922 billion USD in 2013 (Gartner, 2014), of which Indian IT services industry accounted for USD 118 billion (NASSCOM STRATEGIC REVIEW, 2014). These results, therefore, hold promise for generalizability within an industry that is an important component of the global economy. However, a study of capabilities is context-dependent by definition (Teece, Pisano, and Shuen, 1997; Winter, 2003).

Capabilities that are generalizable across industries may be abstract and thus less meaningful for scholars and practitioners in terms of decision making.

Generalizability into other industry contexts is not readily apparent, although the importance of business-domain knowledge is evident in the case of management consulting (e.g., McKinsey, BCG). Management consultants specialize in particular industries as they move up the career ladder to become managing partners in their firms. Domain knowledge also assumes critical importance in architectural design firms. Architects (construction engineers) are domain experts who design buildings based on the requirements of a given industry or client, and developers (and civil engineers) are technology experts who follow the design to build the structure.

We found some evidence justifying investments in general human capital by focal firms. A logical next step is to design a study to examine the implications for rival firms hiring employees with firm-specific skills. Future studies could also examine the impact of firm-specific training and certifications on project and firm performance. Related studies could look at how software project teams that are globally distributed in multiple locations share information, work in tandem, and develop capabilities to deliver value to customers. Other interesting avenues of research could be a study of the impact of offshore outsourcing in the IT services industry as it gradually expands in scale and scope to increasingly higher-end tasks (such as cloud computing, big data analytics, and mobile applications) that require sophisticated skills and capabilities. We hope that our study will provide an impetus to develop contextually grounded capability measures and to tease out the impact of ordinary and dynamic capabilities in different industries.

In conclusion, this paper attempted to establish a link between firm strategy and general human capital investments aimed at capability development. We identified two different capabilities, pointed out convenient modes of developing these capabilities, and estimated their performance impact. Using in-depth interviews and detailed, firm-specific archival data, we depicted the link between strategy, capability development, and firm performance. We hope that this study will encourage future studies to estimate the implications of investing in general and firm-specific learning initiatives in different industries. This type of research will further our understanding of the conditions under which employer-provided general or firm-specific training and certifications create value for firms and therefore maybe prescribed as a best practice. Furthermore, we can also learn which capabilities are important to success in different industries and how they may relate to firm strategy, affect performance, and ultimately result in performance differences among firms.

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article:

Appendix S1. Examples of certification exams administered.

Appendix S2. Evolution of capability-building process at a large Indian *IT* services firm.

Appendix S3. Detailed description of all control variables and project size (function points).

Appendix S4. Robustness tests for final Model 5, Table 2.

Appendix S5. Regression estimates for addressing possible sample selection bias due to project team staffing based on exam scores and experience.