Revista Ciências Administrativas
e-ISSN:2318-0722 Journal of Administrative Sciences
Universidade de Fortaleza

Analysis of the Acquisition Mechanisms and Conversion of Knowledge to the Technological Capacity Accumulation in Brazilian Capital Goods

Análise dos Mecanismos de Aquisição e Conversão de Conhecimento para a Acumulação de Capacidade Tecnológica em Bens de Capital Brasileiros

Análisis de los Mecanismos de Adquisición y Conversión de Conocimiento para la Acumulación de Capacidad Tecnológica en Bienes de Capital Brasileños

10.5020/2318-0722.2025.31.e15000

Marcelo Seido Nagano
Holds a Master's and Ph.D. in Mechanical Engineering from the São Carlos School of Engineering at the University of São Paulo (EESC-USP), and completed a Postdoctorate in Applied Mathematics and Computing at the Associated Laboratory for Computing and Applied Mathematics of the National Institute for Space Research (INPE). He is currently a Researcher and CNPq Productivity Research Fellow (Level 1-B), as well as Editor-in-Chief of international journals: Technology Audit and Production Reserves (TAPR - ISSN: 2664-9969) and Journal of Engineering and Computer Innovations (JECI - ISSN: 2141-6508).

Antonio Iacono
Associate Professor at the Lorena School of Engineering, University of São Paulo (EEL-USP). Holds a Master's and Ph.D. in Industrial Engineering from the University of São Paulo and a Bachelor's degree in Mechanical Engineering from the Federal University of Itajubá.

Tiago Fernando Musetti
Holds a Bachelor's degree in Economics and a Postgraduate Certificate in Business Management from the University of Araraquara (UNIARA). Specialist in Urban Engineering. Holds a Master's degree in Industrial Engineering from the São Carlos School of Engineering, University of São Paulo (EESC/USP). Holds a Ph.D. in Industrial Engineering from the Department of Industrial Engineering at the Federal University of São Carlos (DEP/UFSCar). Completed Postdoctoral research in Industrial Engineering at the São Carlos School of Engineering, University of São Paulo (EESC/USP).

Abstract

This article aims to analyze the learning processes and to identify the knowledge acquisition and conversion mechanisms that contribute significantly to the process of accumulation of technological capacity. In order to achieve these objectives, an exploratory study carried out among 44 companies in the mechanical capital goods sector in Brazil. The contribution of knowledge acquisition and conversion mechanisms was assessed using the Technological Capability Index (TCI), correspondence analysis, and multiple linear regression with stepwise selection. Results indicate varying levels of influence across mechanisms; show that, although such mechanisms are present, they vary in intensity and contribution, reflecting differences in the accumulation of technological capabilities over time. Initiatives related to production capacity expansion, training in production and process techniques, and quality systems are positively associated with the TCI, indicating stronger organizational engagement in process improvement. However, limited interaction with external sources of knowledge, low levels of knowledge sharing, and a reduced degree of codified knowledge recombination are observed. These findings highlight the importance of effectively managing multiple learning mechanisms, as they directly influence the pace and trajectory of technological capability accumulation within firms.

Keywords: *technological learning, technological capability, knowledge acquisition, knowledge conversion, correspondence analysis.*

Resumo

Este artigo tem como objetivo analisar os processos de aprendizagem e identificar os mecanismos de aquisição e conversão de conhecimento que contribuem significativamente para o processo de acumulação de capacidade tecnológica. Para alcançar esses objetivos, foi realizado um estudo exploratório com 44 empresas do setor de bens de capital mecânicos no Brasil. A contribuição dos mecanismos de aquisição e conversão de conhecimento foi avaliada por meio do Índice de Capacidade Tecnológica (ICT), análise de correspondência e regressão linear múltipla com seleção stepwise. Os resultados indicam níveis variados de influência entre *os mecanismos; mostram que, embora tais mecanismos estejam presentes, eles variam em intensidade e contribuição, refletindo diferenças na acumulação de capacidades tecnológicas ao longo do tempo. Iniciativas relacionadas à expansão da capacidade de produção, capacitação em técnicas de produção e processos e sistemas de qualidade estão associadas positivamente ao ICT, indicando um engajamento organizacional mais forte na melhoria de processos. No entanto, observam-se interação limitada com fontes externas de conhecimento, baixos níveis de compartilhamento de conhecimento e um grau reduzido de recombinação de conhecimento codificado. Esses achados destacam a importância de gerenciar eficazmente múltiplos mecanismos de aprendizagem, uma vez que eles influenciam diretamente o ritmo e a trajetória da acumulação de capacidade tecnológica nas firmas.*

Palavras-chave: *aprendizagem tecnológica, capacidade tecnológica, aquisição de conhecimento, conversão de conhecimento, análise de correspondência.*

Resumen

Este artículo tiene como objetivo analizar los procesos de aprendizaje e identificar los mecanismos de adquisición y conversión de conocimiento que contribuyen significativamente al proceso de acumulación de capacidad tecnológica. Para alcanzar estos objetivos, se llevó a cabo un estudio exploratorio en 44 empresas del sector de bienes de capital mecánicos en Brasil. La contribución de los mecanismos de adquisición y conversión de conocimiento se evaluó mediante el Índice de Capacidad Tecnológica (ICT), el análisis de correspondencias y la regresión lineal múltiple con selección stepwise. Los resultados indican diferentes niveles de influencia entre los mecanismos; muestran que, aunque dichos mecanismos están presentes, varían en intensidad y contribución, lo que refleja diferencias en la acumulación de capacidades tecnológicas a lo largo del tiempo. Las iniciativas relacionadas con la expansión de la capacidad de producción, la capacitación en técnicas de producción y procesos, y los sistemas de calidad están asociadas positivamente con el ICT, lo que indica un mayor compromiso organizacional en la mejora de procesos. Sin embargo, se observa una interacción limitada con fuentes externas de conocimiento, bajos niveles de intercambio de conocimiento y un grado reducido de recombinación de conocimiento codificado. Estos hallazgos destacan la importancia de gestionar eficazmente múltiples mecanismos de aprendizaje, ya que influyen directamente en el ritmo y la trayectoria de la acumulación de capacidad tecnológica en las empresas.

Palabras clave: *aprendizaje tecnológico, capacidad tecnológica, adquisición de conocimiento, conversión de conocimiento, análisis de correspondencias.*

Introduction

Since the 1970s, the literature about technology and development has emphasized technological acquisition in developing countries as a crucial determinant of successful industrialization (Romijn, 1997)., To achieve this companies need to develop abilities and experiences to assimilate, use and adapt, improve and create technologies through continuous technological learning processes. However, this transformation represents a major challenge for these countries (Lall, 1992), as the rapid pace of technological advances requires organizational changes and faster innovation processes (García-Sánchez et al., 2018). In this context, the development of technological capabilities is not a passive, mechanical, or automatic process; rather, it is understood as a cumulative and deliberate learning process that involves the accumulation of diverse knowledge and skills (Ge & Liu, 2022).

The processes of acquisition and conversion of knowledge contains different learning mechanisms that influence the trajectory of accumulation of the companies' capacity (Yu & Chen, 2020). According to Jha and Cottam (2021) understanding the functioning of the learning system, through the analysis of the characteristics of the processes of acquisition and conversion of knowledge, practiced by the companies, help in the identification of effective or ineffective systems of learning, and, therefore, in a better direction for the accumulation of technological capacity and consequent improvement of the technical and economic performance of the company over time.

Another important aspect of the learning process in companies operating in late industrialization is that they differ in the manner and speed with which they accumulate technological skills over time (Figueiredo, 2001). Frontier technology companies already have innovative technological competence, while the former operate based on technology acquired from companies in other countries (Figueiredo, 2001, 2003). In this sense, in order to become competitive and to accompany border technology companies becomes necessary initially to acquire knowledge to create and accumulate their own technological competence (Angelidou et al., 2022). Thus, firms that establish continuous learning routines exhibit a greater capacity to absorb new knowledge, improve existing technologies, and develop innovative capabilities than firms whose learning processes occur only sporadically (Jha & Cottam, 2021).

Among the various industrial sectors, the capital goods industry, particularly the machinery and equipment sector, plays a strategic role in industrial and economic development. In addition to embodying high levels of technological knowledge, firms in this sector play a key role in the diffusion of technology by supplying machinery, equipment, and production solutions to virtually all other sectors of the economy. Consequently, their technological capabilities directly influence the productivity, competitiveness, and innovative capacity of industry as a whole. However, these firms face increasing challenges arising from advances in production processes and intensified international competition, making technological learning an essential prerequisite for maintaining competitiveness.

Although the literature recognizes technological learning as one of the main drivers of technological capability accumulation, most studies have focused on measuring technological capabilities or innovation outcomes (Bell & Pavitt, 1995; Figueiredo, 2001; Lall, 1992). Comparatively, less attention has been devoted to understanding how different learning mechanisms contribute to this accumulation process (Zahra et al.,2007). In particular, empirical evidence remains limited regarding the relative contribution of internal knowledge acquisition, external knowledge acquisition, knowledge socialization, and knowledge codification mechanisms to the accumulation of technological capabilities, especially in firms operating in emerging economies and in strategic sectors such as the capital goods industry.

Thus, according to Figueiredo (2001), understanding the functioning of learning systems, through the analysis of the characteristics of knowledge acquisition and conversion processes adopted by firms, enables the identification of more or less effective learning systems. Such analysis contributes to a better understanding of organizational learning mechanisms, providing support for guiding the process of technological capability accumulation and, consequently, for the sustained improvement of firms' technical and economic performance over time.

This gap is particularly relevant because firms operating within the same industry often exhibit markedly different technological development trajectories, even when they face similar competitive conditions. These differences arise not only from access to technologies but also from the way organizational learning systems are structured and managed, particularly about the intensity, continuity, and complementarity of knowledge acquisition and knowledge conversion mechanisms.

Against this background, this study seeks to answer the following research question: How do different technological learning mechanisms—external knowledge acquisition, internal knowledge acquisition, knowledge socialization, and knowledge codification—influence the accumulation of technological capabilities in Brazilian firms operating in the capital goods industry?

To address this research question, this study analyzes firms' technological learning systems by examining knowledge acquisition processes (individual learning) and knowledge conversion processes (organizational learning), as proposed by Figueiredo (2001). Specifically, it seeks to identify the contribution of different learning mechanisms using the Technological Capability Index (TCI), based on Lall (1992) taxonomic framework, thereby identifying the mechanisms that exert the greatest influence on the accumulation of technological capabilities.

This study contributes to literature in three main ways. First, it advances the understanding of technological learning by analyzing the contribution of different learning mechanisms separately, rather than treating organizational learning as a single construct. Second, it expands the empirical evidence on the accumulation of technological capabilities in firms from a late-industrializing country operating in the strategically important capital goods industry, a context that remains underexplored in international literature. Third, it offers managerial and public policy implications by identifying learning mechanisms whose intensification may accelerate the accumulation of technological capabilities and strengthen firms' innovation capacity.

After this introductory section, this paper is organized as follow. Section 2 presents a briefly theoretical reference on technological learning, highlighting the processes and mechanisms for the accumulation of technological capacity. Section 3 presents the indicators for measuring the technological capacity, the TCI - Technological Capacity Index used in this work. Section 4 reports the methodology. Section 5 brings results anddiscussion. Finally, Section 6 presents the conclusions of the study, together with the study's limitations, suggestions for future research, and the managerial and public policy implications.

Literature Review

Technological Capability and the Role of Learning Mechanisms

Technological capabilities are a fundamental component for achieving substantive goals such as a satisfactory quality of life or a higher income, being fundamental component of economic growth and welfare (Ge & Liu, 2022; Yu & Chen, 2020). In the organizational environment, technological capabilities are defined as the resources needed to create and manage technological change, including skills, knowledge, experience and systems (Hou & Nie, 2022; Hansen & Ockwell, 2014).

Through their technological capabilities, organizations accumulate knowledge and skills over time in order to improve their ability to implement and deal with technical changes (Ge & Liu, 2022; Hansen & Ockwell, 2014). In addition, these skills enable the company to promote dynamic and integrative capacity to reconfigure its internal competencies and promote the organizational change needed to meet the demands of the environment in which it is embedded (García-Sánchez et al., 2018). Technologies have a tacit nature involving several individual and collective organizational aspects related to learning that are inserted and are specific to each context in which they are developed (Ge & Liu, 2022; Baginski et al., 2017).

Technological learning is understood as the process of construction and accumulation of technological capacity over time (Kim, 2001), and according to Ge and Liu (2022), it comprises several processes by which individual learning becomes organizational learning. In this context, worth highlighting that organizational learning will require internal elements, which include intra-firm efforts, and external elements, which occur through interaction and contact networks with other organizations (Angelidou et al., 2022; Hou & Nie, 2022). An important distinction that characterizes technological learning refers to the dimensions of knowledge, defined in tacit and codified. In particular, the tacit nature of knowledge is an important aspect of the learning process (Gertler, 2003).

Tacit knowledge is highly personal and refers to technical skills, know-how, experiences, values and the way the world is perceived, which makes it difficult to be formalized and communicated. In turn, the explicit can be stored in documents, manuals, databases and other media; by being formal and systematic, can be easily communicated and shared (Laptev & Shaytan, 2023; Nonaka & Takeuchi, 1995).

The forms of tacit knowledge transfer are strongly related to experience, demonstration, observation, and imitation. However, solely the accumulation of tacit knowledge or codified knowledge, separately, should not lead to the creation of a knowledge base in the company; it is important to consider the interaction of the two dimensions (Ge & Liu, 2022; Laptev & Shaytan, 2023).

Laptev and Shaytan (2023) and Nonaka and Takeuchi (1995) argue that the process of knowledge management and creation must occur from the transformation of tacit knowledge into explicit through a process of dynamic interaction between them and that generates the creation of organizational knowledge.

In the organizational environment, it is relevant to transform individual learning into collective and continuously create new knowledge, requiring a knowledge-based management derived from a comprehensive theory that explains the complex process by which knowledge is created and used in the organization in its interaction with the environment (Ge & Liu, 2022; Nonaka et al., 2000), requiring a knowledge-based management derived from a comprehensive theory that explains the complex process by which knowledge is created and used in the organization in its interaction with the environment (Nonaka et al., 2008).

Organizational knowledge is not simply the sum of individual knowledge; it is formed by unique patterns of interactions between technologies, techniques, and people that cannot easily be imitated by other organizations because these interactions are shaped by the unique history and culture of the organization (Bath, 2001). According to Nonaka and Takeuchi (1995) and Jha and Cottam (2021), the tacit knowledge of the individual is converted into organizational learning through different modes of conversion, intermediates between the dimensions of tacit knowledge and codified knowledge. In such conversions the sharing, structuring and incorporation of knowledge in the individuals of the organization take place.

Accordingly, Errico et al. (2024) suggests that education represents a core component of human capital and plays a significant role in shaping firm performance. The level of formal education among members of the management team reflects the stock of knowledge and skills available within the organization. As such, in the context of learning mechanisms, the formal educational attainment of management team members acts as an enabling factor for knowledge acquisition and conversion processes, underpinning the accumulation of technological capabilities. According to Alzate-Alvarado et al. (2025), human capital and technological capability are important predictors of firm growth.

The concepts as well as the conversion processes are important for the analysis of learning processes in companies from developing countries, enable to possible not only to improve the existing learning processes, but to describe how these processes occur within companies, that is, how they are developed.

Regarding the technological capacity of organizations, Ge and Liu (2022), Hou and Nie (2022) and Yu and Chen (2020) also incorporate the dimension of company interaction and external environment and attach importance to learning mechanisms in the process of accumulation of knowledge. For Yu and Chen (2020) the expansion of knowledge depends on the intensity of learning and prior knowledge, that is, accumulated prior knowledge increases the ability to accumulate more knowledge and learn related concepts more easily.

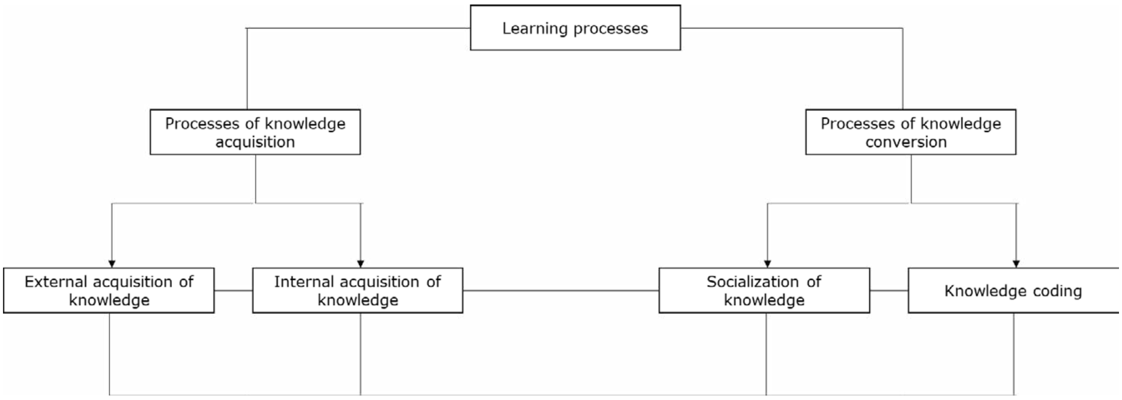
From this perspective, knowledge management provides the organizational foundation through which technological capabilities are developed and accumulated. Technological capabilities do not emerge solely from firms' access to technologies, but rather from their ability to acquire, assimilate, share, codify, and apply knowledge throughout the organization. Therefore, effective knowledge management enables firms to transform individual learning into organizational knowledge, ensuring that technological knowledge is retained, disseminated, and continuously leveraged to support technological capability accumulation and innovation (Nonaka & Takeuchi, 1995; Figueiredo, 2001; Ge & Liu, 2022).

Accordingly, the processes of knowledge acquisition and knowledge conversion constitute the underlying learning mechanisms through which technological capabilities evolve over time. The effectiveness of these mechanisms determines not only the speed with which firms accumulate technological capabilities but also their ability to sustain innovation and respond to technological change. In this sense, knowledge management should be understood not as an end in itself, but as the organizational process that enables the continuous accumulation of technological capabilities.

In summary, the learning processes that allow the accumulation of technological capacity can be divide into two distinct processes: (i) the process of acquisition of knowledge, related to learning at the individual level, which can be decomposed into processes of acquisition of external knowledge and processes of acquisition of internal knowledge. (ii) the process of knowledge conversion, related to organizational learning, which can be disaggregate into the socialization of knowledge and codification of knowledge (Figueiredo, 2001; Yu & Chen, 2020). A representation of these learning processes (and adopted in this study) is shown in Figure 1.

Figure 1

Technological Learning Processes



Note. Adapted by Figueiredo (2001)

External acquisition of knowledge

The processes by which individuals acquire tacit and/or codified knowledge coming from outside the company are known as processes of external acquisition of knowledge (Yu & Chen, 2020). According to Figueiredo (2009) and Ge and Liu (2022), as companies belonging to developing countries start in a resource-poor condition, they need to seek external knowledge in order to build up and accumulate their own capacities, whether production or innovation. However, for the company to build the capacities and obtain different types of knowledge required, it demands sustained, organized and effective efforts.

The main forms of learning generated by external sources are imitation learning and interaction learning (Ge & Liu, 2022). Learning-by-imitating is generated from the reproduction of innovations introduced by other companies, in an autonomous and non-cooperative way. It is not being exactly a replica, the company needs to be internally trained to perform reverse engineering (Cassiolato, 2004). Learning-by-interacting refers to the systematic flow of information. The deepening of learning by interaction presupposes a certain selectivity in the relationships between companies, a certain time for the strengthening of trust between the agents, and a system of incentives that induce the process (Olamade, 2001).

Internal acquisition of knowledge

The processes of internal acquisition of knowledge refer to the processes by which people acquire tacit knowledge by performing different activities in the company, for example, performing routine tasks or improving processes and organization of production, equipment and existing products (Hou & Nie, 2022). The importance to bring the knowledge acquired externally is to increase the capacity of the companies themselves to carry out different types of innovative activities (Figueiredo, 2009; Hou & Nie, 2022). It is worth mentioning that internal learning is a necessary condition for external learning, that is, the company must be able to receive, elaborate and assimilate new external knowledge (Cassiolato, 2004; Hou & Nie, 2022).

The main forms of learning generated by internal sources are learning by use, learning by experience, and learning by research. Learning-by-using is related to the company's adaptation to new technologies. Learning-by-doing is considered a key factor in the accumulation of knowledge that leads to innovation, as highlighted in Benedito et al. (2014). The company learns through its own production, in other words, the technology in this case is a function of the experience of each company in the production of the different goods. (Hou & Nie, 2022). Learning-by-searching takes place through formal R & D activities aimed at creating new knowledge.

Socialization of knowledge

Conforming to Figueiredo (2001), the processes of knowledge socialization refer to the processes by which individuals share their tacit knowledge (mental models and technical aptitudes). In other words, any formal or informal process by which tacit knowledge is transmitted from one individual to another, which may involve observation, meetings, joint problem solving, and task turnover.

According to Kogut and Zander (1992), the transfer of know-how and information often requires interaction within small groups, often through the development of a single language or code. The knowledge of a group is not limited simply to knowing the information, but also consists of how the activities should be organized. It is the sharing of a common pool of knowledge, both technical and organizational, that facilitates the transfer of knowledge within groups.

Knowledge coding

As reported by Figueiredo (2009), the processes of knowledge codification are those by which the individual tacit knowledge (or part of it) is express in definitive concepts. In other words, the process by which tacit knowledge is articulated in explicit concepts, in organized and accessible formats and procedures, making it easier to understand, easier to assimilate, and thus facilitating the dissemination of knowledge in the company.

Through the coding mechanisms that knowledge can be transformed into information, where information is in the form of messages, or identifiable sets of rules and relations that can be transmitted to decision makers (Prencipe & Tell, 2001). Coding allows for gains through new combinations of inventories of codified knowledge (Teece, 2007). The main mechanisms of knowledge coding may involve, for example, the standardization of production methods, documentation and internal seminars.

It is important to highlight, according to Figueiredo (2003, 2009), that the organization of training modules by internal staff can involve both socialization processes and knowledge codification. In other words, it is through these two types of processes that the conversion of individual learning into organizational learning takes place. From the above, it can be stated that, as highlighted by Fuentes-Fernández et al. (2024) emphasizes the use of firms' capabilities of knowledge acquisition, assimilation, transformation, and exploitation as a way to improve their innovative performance, while also leveraging available resources and contacts and relying on entities such as business associations to expand their networks of valuable knowledge sources.

Technological Capacity: Indicators for Measurement

In a simple way, as shown in Yam et al. (2011), the capacity for technological innovation can be defined as a set of characteristics that facilitate and support the companies' technological innovation strategies. In a broader definition, technological capacity, according to Hou and Nie (2022), consists of the resources needed to generate and manage technical changes, and especially includes skills, knowledge, experiences and institutional structure. These resources are stored and accumulated in at least three components: human capital, organizational system and technical-physical systems (Figueiredo, 2014).

One of the most elaborate taxonomies of technological capacity at the enterprise level is that of Lall (1992). According to Molina-Domene and Pietrobelli (2012), Lall's taxonomy of technological capabilities has been used successfully in a case study to assess levels of technological development at the enterprise level in developing countries (Lall 1992; Romijn, 1997). At the enterprise level, Lall (1992) taxonomy captures several aspects of technological capability. In this work two main types were considered: production capacities and external link capacities.

Production capacities and external link capabilities

Production capacities refer to the skills and knowledge required for the operation of production facilities. It interlards from basic technology skills, such as quality control and inventory, operation and maintenance, to the more advanced skills such as improvement or adaptation to research, design and innovation (Egbetokun et al., 2012; Hou & Nie, 2022). These processes refer to process engineering, product engineering and industrial engineering (Lall, 1992). This implies the mastery of technologies and, among other things, less or greater innovation. They cover both the process and product technologies, as well as the monitoring and control functions included in industrial engineering. The skills involved determine not only how technologies are exploited and improved, but also how internal efforts are used to absorb technologies purchased or imitated from other companies (Angelidou et al., 2022).

External link capabilities refer to the skills needed to convey information, skills, and technology to receive knowledge from components or suppliers of raw materials, service companies, consultants, and technology institutes. It focuses on the heterogeneous agents that develop interactions of a marketing or non-market character for the generation, adoption and use of new (or already established) specific technologies and for the creation, production and use of new products pertinent to the sector. It involves the analysis of clients, suppliers, manufacturers, universities, financial institutions, government agents, among others (Lall, 1992; Olamade, 2001). This acquisition of technological knowledge from external sources is considered fundamental to the search for competitive advantage (Sherwoo & Covin, 2008).

Such connections affect not only the company's productive efficiency (allowing it to specialize more fully), but also the diffusion of technology. The importance of extra market links to promote productivity growth is recognized in the literature of developed countries.

Methodology

Methodological Procedure

The purpose of this study is to analyze the learning processes for the accumulation of technological capacity. The sample of this study comprised 44 firms in the capital goods sector with more than 20 years of market presence and at least 50 employees, of which 79.5% were small and medium-sized enterprises and 20.5% were large firms.

The firms were selected and classified into four subsectors according to the National Classification of Economic Activities (CNAE 2.0): CNAE 28.1 – Manufacture of engines, pumps, compressors, and transmission equipment; manufacture of general-purpose machinery and equipment; CNAE 28.4 – Manufacture of machine tools; and CNAE 28.6 – Manufacture of machinery and equipment for specific industrial use. The selection of these subsectors is justified by their representativeness in Gross Fixed Capital Formation (GFCF), accounting for approximately 70%.

The Southeast region was selected, particularly the state of São Paulo, as it concentrates the majority of firms in the sector, representing between 55% and 80% of national production, depending on the subsector, according to data from the Brazilian Institute of Geography and Statistics (IBGE). The state of São Paulo, in particular, accounts for between 60% and 85% of the Southeast region's production.

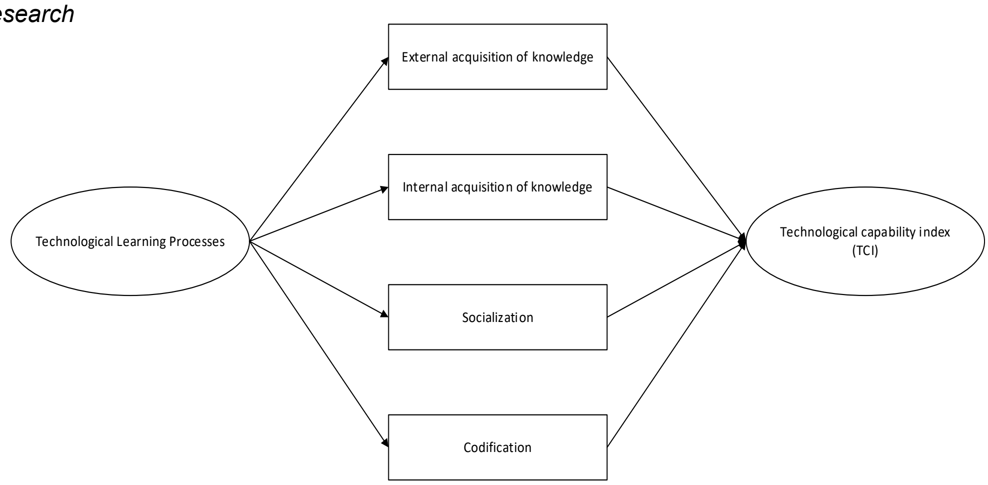
This work made use of several sources of evidence. As a data collection instrument, a script for interviews was used, subdivided into two parts: the first part aimed to compose the Technological Capability Index, and the second part comprised questions aimed at analyzing the technological learning processes presented by companies. The interviews were attended with 52 people among directors, managers and technicians of the respective areas of interest. Among the firms, eight had more than one respondent in order to obtain complete information.We also used document analysis that included reports and records organized in a database. Thereby, the hypothesis set forth in this paper is: All the variables that compose the processes are positively correlated to the process of accumulation of technological capacity in established companies.

As already pointed out in Figueiredo (2001), the four types of learning processes, presented in Figure 1, contain different mechanisms that influence the technological accumulation trajectory of companies.

In this way, this work proposes a research structure in which these four types of learning processes point an important role in promoting the technological capacity of established companies. Figure 2 shows the analytical structure of this study.

Figure 2

Structure of research



Note. The authors themselves

Variables

In order to analyze the contribution of the learning processes to the accumulation of technological capacity, a Technological Capacity Index (TCI) was used based on the taxonomy variants of Lall (1992). According to Molina-Domene and Pietrobelli (2012), Lall's taxonomy of technological capabilities has been used successfully in a case study to assess levels of technological development at the enterprise level in developing countries (Lall 1992; Romijn, 1997). This index has been widely adopted to operationalize the technological capacity at the company level, with emphasis on the studies of Molina-Domene and Pietrobelli (2012) and Romijn (1997). To compose the index, the measured variables were grouped in process engineering, product engineering, quality engineering and development of external links. Capturing the different levels of competence (low, medium and high), as shown in Appendix A, we used categorical variables 0 (none), 1 (ad-hoc) and 2 (systematic).

Each company was assigned a score based on their level of competence. The maximum score is 38 points for the capacity, considering a total of 19 variables, can be obtained by summing the maximum value of the degree of competence presented in each function. The results were then normalized between 0 and 1 to provide the ICT. The Table presented in Appendix B shows the distribution of the TCI score frequencies for the 44 companies investigated.

In order to evaluate the contribution of the learning processes to the process of accumulation of technological capacity, the intensity in which the processes occur in the companies was adopted as measurement value. Intensity is understood as the frequency with which the processes of learning are created, updated, used and perfected over time.

According to Figueiredo (2001, 2009), sporadic learning processes probably will not lead to an effective acquisition of knowledge or to its incorporation in the organizational plane. Over time, certain practices can be routinized and become part of the daily routine of the company. In this sense, intensity is important because it can guarantee a constant flow of external knowledge to the company, and ensure the constant conversion of individual learning into organizational learning. In other words, the functioning of the learning system can have practical consequences for the company's technological competence accumulation trajectory and thus for the operational performance improvement index over time.

The measures of intensity adopted for this study were adapted from Figueiredo (2001, 2009) and constitute four indications, namely: (0) absence of mechanism; (1) rare; (2) intermittent, and (3) continuous.

Results and discussions

This section presents the results of the analysis build in statistical software *R* version 3.5.1. In order to analyze the contribution of the variables that constitute the four types of learning processes for the accumulation of technological capacity, correspondence analysis and multiple linear regression with selection of stepwise variables was used.

The assumptions of the model were examined, including normality, linearity, and multicollinearity. To diagnose potential multicollinearity issues, the Tolerance Index and the Variance Inflation Factor (VIF) were calculated for each variable. The collected data were subjected to a reliability test using Cronbach's alpha coefficient, as shown in Table 1.

Table 1

Reliability of the Scales Used

Learning Processes	Tolerance	VIF	Alpha de Cronbach
External knowledge acquisition	0.604–0.898	1.14–1.656	0.717
Internal knowledge acquisition	0.369–0.790	1.266–2.709	0.711
Knowledge socialization	0.732–0.846	1.182–1.366	0.763
Knowledge codification	0.709–0.874	1.144–1.409	0.669

Note. Authors' own elaboration.

The tolerance and VIF values are within acceptable thresholds, according to Hair et al. (2009), indicating no evidence of multicollinearity. In addition, the Cronbach's alpha values are deemed acceptable, as they exceed 0.60, following the criteria suggested by Field (2013).

The purpose of correspondence analysis is to explore relationships among qualitative variables (or categorical data). It provides an analysis for summarizing and easier visualizing data set in two-dimension plots further. The multiple regression also applied in this paper has the objective of to learn more about the relationship between independent variables and a dependent or criterion variable.

Processes of external acquisition of knowledge

As already presented, the main characteristic adopted to analyze the learning processes involves the intensity in which the mechanisms occur in the organization. The results are show in Table 2.

Table 2

Frequency of variables - Learning mechanisms for the process of acquisition of external knowledge

Learning Mechanisms	Absent	Rare	Intermittent	Continuous
EK1- Specialists (technical consultants)	9%	25%	25%	41%
EK2-External trainings to keep employees up-to-date	7%	32%	30%	32%
EK3-Training Abroad	48%	18%	7%	27%
EK4 - Participation conferences in Brazil	9%	20%	18%	52%
EK5- Participation conferences abroad	50%	18%	14%	18%
EK6 -Scholarship grant	23%	18%	20%	39%
EK7-Access / use of the region's educational infrastructure	25%	11%	34%	30%
EK8 - Customer interaction	0%	0%	14%	86%
EK9 - Supplier Interaction	0%	0%	16%	84%
EK10 - Scientific Research Contacts	52%	36%	9%	2%

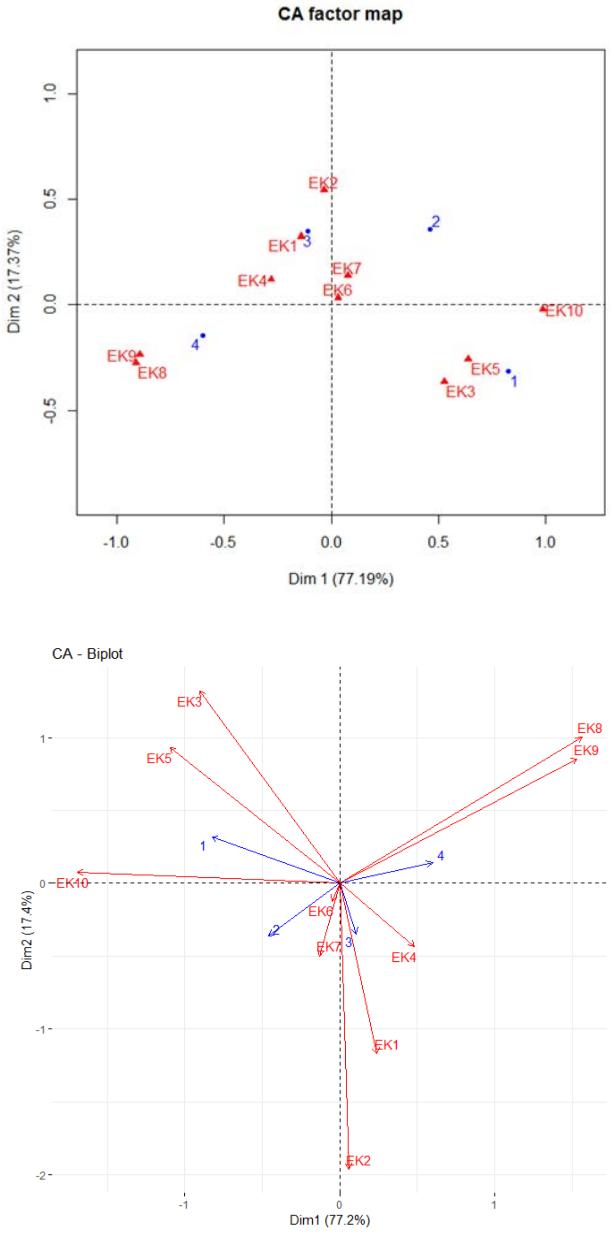
Note. The authors themselves

The first step in correspondence analysis is to observe the chi-square value, this value means the association between row and column variables and the p-value for statistical significance. For this type of process, the chi- square is high meaning a strong and significantly correspondence betwixt row and column variable. Further, examine the eigenvalues to determinate the number of axis to be considered. Eigenvalue is resembled to the amount of information retained by each axis. Dimensions are organized decreasingly and catalogued according to the amount of variance explained. Dimension 1 explains the most variance in the solution, followed by dimension 2.

For this paper are considered a good variance 80% or more, in all the cases, 2 dimensions have been used. The figure 3 shows the symmetric plot (a), an easy way to visualize the measure of their similarity (or dissimilarity) between row and column. In the graph, the columns are represented by the variables and the row by the numbers (acronyms of intensity measurements). Points with similar characteristics are closed on the factor map, the same happen with the column points.

Figure 3

(a) CA map and (b) biplot of variables external knowledge



Note. The authors themselves

EK1 - Specialists (technical consultants), EK2-External trainings to keep employees up-to-date, EK4- Participation conferences in Brazil shows similarity to intermittent (3) in the data set. While EK5- Participation conferences abroad, EK3-Training Abroad are absent (1). The biplot (b) shows that EK8- Customer interaction have an important contribution to the positive pole of the first dimension while EK3-Training Abroad and EK5-Participation conferences abroad have a negative contribution in first dimension. The dimension 2 is mainly defined by EK2-External trainings to keep employees up-to-date. Also is possible to extract of this graph the degree of association between the variables, if the angle between two arrows is acute, then there is a strong association between the corresponding row and column as EK1-Specialists (technical consultants) and EK4-Participation conferences in Brazil.

Table 3

Shows the multiple regression after stepwise to select the significates variables.
Multiple regression of external knowledge

Min	1Q	Median	3Q	Max
-0.30355	-0.12026	0.01402	0.10884	0.40478
Estimate		Std. Error	t value	Pr(>|t|)
(Intercept)	0.85668	0.19136	4.477	7.01e-05 ***
EK3	0.04768	0.02953	1.615	0.11491
EK5	0.04519	0.02557	1.767	0.08540 .
EK6	0.03508	0.02366	1.483	0.14666
EK7	0.08402	0.02503	3.357	0.00183 **
EK9	-0.21945	0.07127	-3.079	0.00390 **
EK10	0.09653	0.03949	2.445	0.01938 *

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Residual standard error: 0.1598 on 37 degrees of freedom
Multiple R-squared: 0.6967, Adjusted R-squared: 0.6475
F-statistic: 14.17 on 6 and 37 DF, p-value: 2.636e-08

Note. The authors themselves

The F-statistic and the associate p-value 2.636e-08 announce that this model is strongly significant, that is, one of the predictor variables is significantly related to the outcome variable, TCI. EK7-Access / use of the region’s educational infrastructure (0.00183), EK9-Supplier Interaction (0.00390), EK10-Scientific Research Contacts (0.01938) are significant at the level of significance 0.1, 0.1 and 0.05 respectively for the process of external acquisition of knowledge. This model explains 64.75% of the variance in the outcome variable and the residual standard error is 0.1598 meaning a good precision of this model.

However, it is important to highlight according to Adam (2023) that Small and medium-sized enterprises (SMEs) face limitations in their innovation capabilities due to difficulties in accessing and benefiting from knowledge from various external sources. In this sense, external knowledge represents an essential strategic resource for improving performance, developing innovations, and enhancing competitiveness. However, the limited diversity of knowledge sources may restrict these capabilities, highlighting the need for greater exploitation of external knowledge sources and for policies that encourage innovation development in SMEs.

Processes of internal acquisition of knowledge

Regarding internal knowledge acquisition processes, the observed results on the intensity with which these mechanisms occur within the organization are presented in Table 4.

Table 4

Learning mechanisms for the process of acquiring internal knowledge

Learning Mechanisms	Absent	Rare	Intermittent	Continuous
IK1 - Inorou-se training of production and process techniques	18%	18%	30%	35%
IK2 - R&D Activities	13%	28%	30%	30%
IK3 - Internal training in TQM and quality system	25%	15%	25%	35%
IK4 - Formation of QCC groups – Quality Control Circle	45%	25%	10%	20%
IK5 - *Design and Process* Software Training	20%	20%	30%	30%
IK6 - Studies to increase production capacity	25%	23%	20%	33%
IK7 - Product Reverse Engineering	40%	18%	23%	20%

Note. Authors’ own elaboration

The chi-square value in table 5 show a value of 27.05, meaning a weak correspondence between the variables and the p-value 0.07 > 0.05 not significantly.

Table 5

Eigenvalue and statistical significance for internal knowledge

	Dim.1	**Dim.2**	**Dim.3**
Variance	0.070	0.011	0.007
% of Var.	79.233	12.374	8.394
Cumulative % of Var.	79.233	91.606	100.000
χ^2		27.057	
P - value		0.07792	

Note. The authors themselves

For this analysis also two dimensions was enough. The variable IK1-Internal training of production and process techniques, IK5-Training in project and process software's and IK3-TQM internal training and quality system shows similarity to continuous (4) in the data set. While IK6-Studies to increase productive capacity with rare (2). The biplot (b) shows IK1-Internal training of production and process techniques and IK5-Training in project and process software's are highly correlated. The same occurs with IK2-R & D Activities and IK6-Studies to increase productive capacity.

IK3-TQM internal training and quality system seems the most important variable to the contribution to the positive pole at the first dimension and IK7-Reverse Engineering of Products to the negative pole. The dimension 2 is defined by IK4-Formation of CCQ groups and IK2-R & D Activities, negative and positive pole respectively.

Is possible to observe in table 6, the multiple regression model created after stepwise.

Table 6

Multiple regression of internal knowledge

Min	1Q	Median	3Q	Max
-0.185824	-0.05088	-0.009313	0.070469	0.177152
Estimate		Std. Error	t value	Pr(>|t|)
(Intercept)	-0.04494	0.04795	-0.937	0.35468
IK1	0.05652	0.01804	3.133	0.00338 **
IK2	0.0816	0.01676	4.868	2.12e-05 ***
IK3	0.04289	0.01993	2.152	0.03802 *
IK4	0.03105	0.01928	1.61	0.11581
IK5	0.0723	0.0158	4.575	5.20e-05 ***
IK6	0.08052	0.01498	5.374	4.42e-06 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				
Residual standard error: 0.09471 on 37 degrees of freedom				
Multiple R-squared: 0.8934, Adjusted R-squared: 0.8761				
F-statistic: 51.68 on 6 and 37 DF, p-value: < 2.2e-16				

Note. - The authors themselves

The F-statistic and the associate p-value 2.2e-16 announce that this model is strongly significant to the outcome variable, TCI. Almost all the variables used to explain internal acquisition of knowledge are significant except IK4-Formation of CCQ groups. This model explains 89.34% of the variance in the outcome variable and the residual standard error is 0.8934 meaning a good precision of this model corresponding to 15% error rate.

Processes of socialization of knowledge

Regarding internal knowledge acquisition processes, the intensity with which these mechanisms occur within the organization is presented in Table 7.

Table 7

Learning mechanisms for the process of socialization of knowledge

Learning Mechanisms	Absent	Rare	Intermittent	continuous
SO 1 - Dissemination of interactive practices for problem solving	8%	25%	23%	45%
SO 2 - Dissemination of externally received training	13%	33%	25%	30%
SO 3 - Constitution of teams for the treatment of anomalies	25%	23%	15%	38%
SO 4 - Process and Product Audits	35%	3%	23%	40%
SO 5 - Operational Work Diagnostic System	35%	23%	20%	23%
SO 6 - Hiring and development of *trainee engineers*	45%	18%	20%	18%
SO 7 - On-the-job training	15%	18%	23%	45%
SO 8 - Improvement Suggestion System	20%	23%	25%	33%
SO 9 - Implementation of suggestions	23%	28%	20%	30%

Note. Authors' own elaboration

The P-value in table 8 show a value of 0.0027, significantly variables for this process of knowledge. It presents a good correspondence between the variables with the chi-square 47.7224. The two dimensions explain 95% of the variance.

Table 8

Eigenvalue and statistical significance for socialization of knowledge

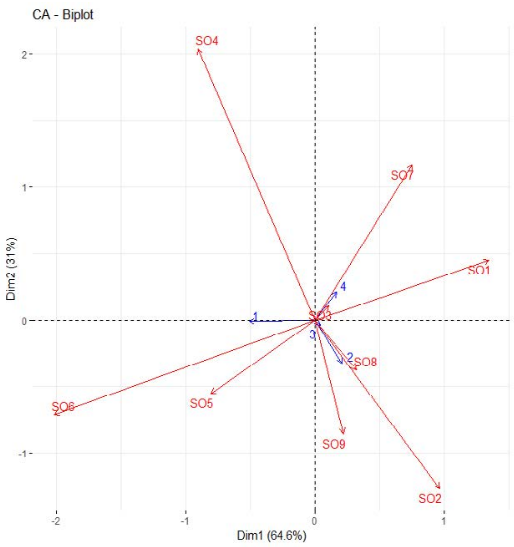
	Dim.1	Dim.2	Dim.3
Variance	0.078	0.037	0.005
% of Var.	64.560	31.050	4.390
Cumulative % of Var.	64.560	95.610	100.000
χ^2		47.72243	
P - value		0.002731542	

Note. The authors themselves

In figure 4 is possible to observe the variables SO8 - System suggestions for improvements and SO9-Implementation of suggestions shows similarity to intermittent (3) in the data set. While SO1- Dissemination of practices and SO7-on-the-job training with continuous (4). The biplot (b) shows that SO2-Dissemination of trainings received externally and SO9-Implementation of suggestions are highly correlated. Exactly happens to SO1-Dissemination of practices and SO7-on-the-job training.

Figure 4

(a) CA map and (b) biplot of variables of socialization of knowledge



Note. The authors themselves

The SO4-Process and product audit is the most important variable to the contribution to the negative pole at the first dimension. The dimension 2 is defined by SO6-Counting and development of trainee engineers and SO2-Dissemination of trainings received externally, negative and positive pole respectively.

Table 9, the multiple regression model created after stepwise to select the model show the F-statistic and the associate p-value 3.138e-15 meaning that this model is very significant to the outcome variable, TCI.

Table 9

Multiple regression of socialization of knowledge

Min	1Q	Median	3Q	Max
-0.1893	-0.06198	0.001941	0.06512	0.20652
Estimate		Std. Error	t value	Pr(>|t|)
(Intercept)	0.05122	0.04373	1.171	0.24892
SO2	0.0619	0.01733	3.571	0.00101 **
SO4	0.03111	0.01647	1.889	0.06676 .
SO5	0.06025	0.01829	3.295	0.00218 **
SO6	0.04356	0.01681	2.592	0.01358 *
SO7	0.09202	0.01848	4.98	1.5e-05 ***
SO8	0.03008	0.0145	2.075	0.04501 *

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Residual standard error: 0.1026 on 37 degrees of freedom
Multiple R-squared: 0.8748, Adjusted R-squared: 0.8545
F-statistic: 43.09 on 6 and 37 DF, p-value: 3.138e-15

Note. The authors themselves

All the variables selected used to explain processes of socialization are significant with different levels of significance. This model explains 87.48% of the variance in the outcome variable and the residual standard error is 0.1026 a good precision of this model corresponding to 17% error rate.

Processes of codification of knowledge

The extent to which internal knowledge acquisition mechanisms occur within the organization is presented in Table 10.

Table 10

Learning mechanisms for the process of encoding knowledge

Learning Mechanisms	**Absent**	**Rare**	**Intermittent**	**continuous**
CO 1 - Standardization of activities and processes	3%	10%	25%	63%
CO 2 - Technical assistance reports	5%	3%	10%	83%
CO 3 - Anomaly Analysis Reports	13%	13%	18%	58%
CO 4 - Internal Process and Product Audit Report	28%	13%	8%	53%
CO 5 - Elaboration of technical procedures	5%	10%	30%	55%
CO 6 - Standard operating procedures	5%	10%	20%	65%
CO 7 - Consultation of competitor products and manuals	18%	13%	25%	45%
CO 8 - Industrial Standards	0%	8%	18%	75%

Note. Authors’ own elaboration

The chi-square value in table 11 show a value of 76.874, a great value for correlation between the variables and the p-value 2.6704E-08 < 0.05 significantly. It is concluded a good analysis. The two dimensions is equal to 97% of the variance explained.

Table 11

Eigenvalue and statistical significance for codification of knowledge

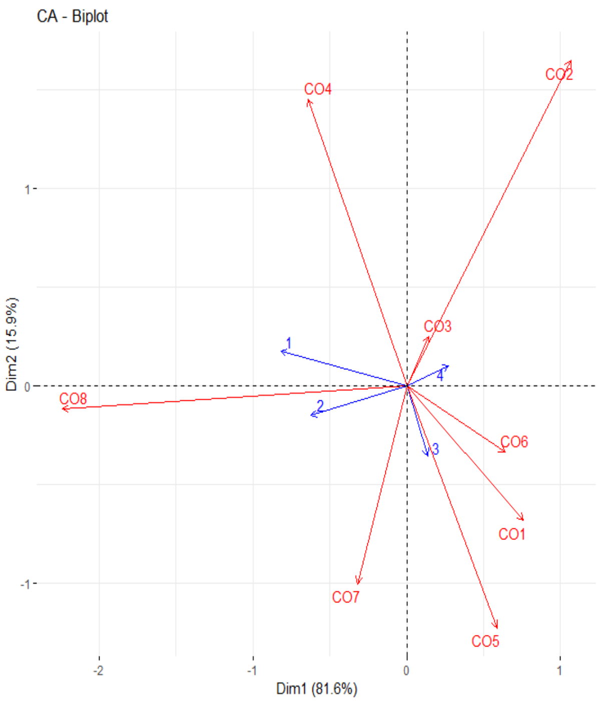
	Dim.1	Dim.2	Dim.3
Variance	0.178	0.035	0.006
% of Var.	81.611	15.851	2.538
Cumulative % of Var.	81.611	97.462	100.000
χ^2		76.87409	
P - value		2.6704E-08	

Note. The authors themselves

In figure 5 is possible to observed the variables CO1-Standardization of activities and processes, CO3-Anomaly Analysis Reports, CO4-Internal audit of process and product and CO6-Standard operating procedures show similarity among them and the variable continuous (4) in the data set. While CO5-Elaboration of technical procedures and CO7-Queries competitors' products and manuals with the variable intermittent (3).

Figure 5

(a) CA map and (b) biplot of variables of codification of knowledge



Note. The authors themselves

The biplot (b) in figure 6 shows CO1-Standardization of activities and processes and CO6-Standard operating procedures are correlated.

Figure 6

(a) CA map and (b) biplot of variables internal knowledge

Note. The authors themselves

As CO2-Technical assistance reports and CO3-Anomaly Analysis Reports are much correlated. CO2-Technical assistance reports seems the most important variable to the contribution to the positive pole at the first dimension and

CO4-Internal audit of process and product to the negative pole. The dimension 2 have more contribution by CO5-Elaboration of technical procedures to positive pole and CO8-Industrial standards to negative pole.

Table 12, the multiple regression model with selected variables model show the F-statistic and the associate p-value 2.761e-09 that content this model is highly significant to the outcome variable, TCI.

Table 12

Multiple regression of codification of knowledge

Min	1Q	Median	3Q	Max
-0.26129	-0.10877	-0.01744	0.11709	0.33838
Estimate		Std. Error	t value	Pr(>|t|)
(Intercept)	-0.16903	0.09468	-1.785	0.081996 .
CO1	0.09301	0.04727	1.968	0.056239 .
CO5	0.11211	0.03421	3.277	0.002210 **
CO6	0.0642	0.03928	1.634	0.110252
CO8	0.08133	0.02242	3.628	0.000818 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				
Residual standard error: 0.1592 on 39 degrees of freedom				
Multiple R-squared: 0.6824, Adjusted R-squared: 0.6499				
F-statistic: 20.95 on 4 and 39 DF, p-value: 2.761e-09				

Note. The authors themselves

Almost all the variables selected used to explain processes of codification are significant with different levels of significance except CO6-Standard operating procedures. This model explains 68.24% of the variance in the outcome variable, and the residual standard error is 0.1592 a good precision of this model corresponding to 26 % error rate despite to not very high R-square.

The findings of this study reinforce the evidence that learning is one of the main determinants of firms' technological capabilities. Firms that institutionalize continuous learning processes exhibit greater adaptive and innovative capacity, corroborating the importance of the continuity of learning mechanisms observed in this study.

Regarding external knowledge acquisition, the findings reveal a limited contribution of external knowledge acquisition mechanisms to the accumulation of technological capabilities. This result suggests that the firms investigated maintain limited interaction with external sources of knowledge, such as universities, research centers, suppliers, customers, competitors, and other organizations within the innovation ecosystem. Consequently, technological learning tends to remain predominantly based on internal sources, restricting access to new knowledge, particularly tacit knowledge and knowledge involving higher levels of technological complexity.

According to Tu et al. (2006) and Liao et al. (2010), the limited use of external knowledge acquisition mechanisms indicates constraints on firms' ability to access more advanced technological knowledge. These authors emphasize that learning from customers, suppliers, universities, and other organizations is essential for enhancing firms' ability to assimilate and transform knowledge into innovation capabilities.

This evidence is consistent with recent literature, as reported by Pinto et al. (2023), which recognizes external knowledge acquisition as one of the main antecedents of innovation and the renewal of technological capabilities. Review studies show that innovative firms systematically combine internal and external knowledge by using collaborative networks, strategic alliances, universities, research institutes, and suppliers as complementary sources of knowledge for technological development.

Similarly, García-Vega and Vicente-Chirivella (2024) demonstrate that the limited use of external knowledge acquisition mechanisms may reduce firms' opportunities to access scientific and technological knowledge generated by universities and research institutes, thereby limiting their innovative potential.

With respect to internal knowledge acquisition, this study identified the greatest diversity of learning mechanisms, although their intensity remained low, indicating that continuous learning processes have not yet been fully internalized. The predominance of internal knowledge acquisition mechanisms observed in this study is consistent with Figueiredo (2002), who identifies these mechanisms as fundamental to the initial development of technological capabilities. However, the low intensity with which these activities are carried out suggests that learning still occurs in a discontinuous manner, thereby limiting the pace of technological capability accumulation. Although Figueiredo (2002) considers internal mechanisms essential for the development of technological capabilities, their relatively high contribution in this study was not sufficient to foster continuous learning, indicating that the mere existence of such mechanisms does not guarantee their effectiveness.

Likewise, Tacla and Figueiredo (2006) show that firms that develop continuous routines for training, engineering activities, and problem-solving are able to progress more rapidly toward innovative technological capabilities.

Regarding knowledge socialization processes, the results indicate a limited use of mechanisms aimed at collective learning. Although on-the-job training is relatively more frequent, collaborative practices such as problem-solving teams and employee suggestion systems for continuous improvement are rarely adopted. These findings suggest that the organizations prioritize individual forms of learning over mechanisms that promote the collective construction of knowledge.

Empirical studies have shown that practices such as teamwork, collaborative problem-solving, and employee participation constitute important knowledge socialization mechanisms, fostering organizational learning and improving organizational performance.

Yuen and Lam (2024) demonstrate the fundamental role of knowledge sharing within firms in enhancing innovation capability performance. The limited use of these mechanisms may restrict the dissemination of tacit knowledge among employees and constrain the development of organizational capabilities.

A similar pattern is observed with respect to knowledge codification, corroborating the findings of Figueiredo (2002). Knowledge codification represents one of the four pillars of technological learning. Firms that systematically document procedures, experiences, and solutions accumulate knowledge more rapidly because they reduce knowledge losses associated with employee turnover and facilitate organizational learning, thereby supporting the accumulation of technological capabilities.

These findings can also be interpreted in light of Zollo and Winter (2002), who identify knowledge codification as one of the key mechanisms of organizational learning. According to these authors, the systematic documentation of experiences, procedures, and routines preserves organizational knowledge, reduces dependence on individual knowledge, and supports the evolution of organizational capabilities. Therefore, the low frequency of knowledge codification mechanisms observed in this study may limit knowledge retention and dissemination, ultimately constraining the accumulation of technological capabilities.

Although internal knowledge acquisition mechanisms made the greatest contribution to technological capability, the findings suggest that the low intensity of external knowledge acquisition, knowledge socialization, and knowledge codification mechanisms may reduce the overall effectiveness of the technological learning process, since these mechanisms operate in a complementary manner in the accumulation of technological capabilities (Bell & Pavitt, 1995; Figueiredo, 2002).

Conclusion

When considering the different types of learning, it can be observed that, although the analyzed mechanisms are present, they exhibit varying levels of intensity and contribution in explaining the Technological Capability Index (TCI). Identifying these particularities is crucial, as they reflect differences in the accumulation of technological competencies acquired by firms over time.

The greatest diversity of mechanisms contributing to the TCI is observed in internal knowledge acquisition processes, indicating that the sampled firms emphasize control over their production and process routines through initiatives aimed at increasing productive capacity, training in production and process techniques, and quality systems. However, the frequencies observed for these mechanisms are still considered low. Continuous activities are verified in approximately only one-third of the firms. Nonetheless, it is important to highlight that the presence of these mechanisms develops competencies necessary for the operation of existing technologies and for the exploration of new ones.

Regarding external knowledge acquisition processes, the limited contribution of a few learning mechanisms reflects the low interaction of the investigated firms with the external environment for acquiring new knowledge, particularly tacit knowledge. The low contribution of various external learning mechanisms indicates a greater focus on local markets, where the demand for advanced technologies is lower, and a lesser engagement with international markets.

Concerning knowledge socialization processes, low adherence to learning mechanisms is also observed. Knowledge sharing through group activities is minimal, with an emphasis placed primarily on on-the-job training. Important mechanisms for knowledge sharing, such as forming teams to address anomalies and suggestion systems for improvements, occur with low frequency.

A similar pattern is observed regarding knowledge codification processes. Emphasis is placed on maintaining processes and developing technical procedures, which are considered essential for firms in this sector. The absence of other learning mechanisms, such as consulting competitors' products and manuals, anomaly analysis reports, and technical assistance documentation, hinders the accumulation of new combinations of codified knowledge. It is important to underscore that promoting both knowledge socialization and codification processes is fundamental for converting individual knowledge into organizational knowledge.

The literature, as seen, suggests that activities, when continuous, enable the creation, updating and improvement of learning processes over time, guarantee a constant flow of external knowledge of the company; make it better understood the technology acquired and the principles inherent in the processes of acquisition of internal knowledge; and ensure the constant conversion of individual learning into organizational learning. The effective management of various mechanisms of technological learning is crucial as it impacts the way and speed by which a company accumulates its technological capabilities throughout its trajectory. The commitment of a company to organizational learning and knowledge management can promote its technological capacity.

Overall, the results indicate the need for the recognition of—and the development of—public policy instruments aimed at the foundations of innovation processes, namely innovation capability, through the promotion of learning mechanisms. When formulated, such policies should take into account firm heterogeneity and their organizational specificities; otherwise, they are likely to yield limited effectiveness.

On the other hand, greater effort is also required on the part of firms to better understand the development of learning mechanisms. Both those related to knowledge acquisition (external and internal) and those associated with knowledge conversion (socialization and codification) should be equally emphasized by firms. Isolated effective outcomes in only one dimension of knowledge will not be sufficient for the accumulation of the technological capabilities required to achieve a higher level of technological development and competitiveness, whether in domestic and/or international markets.

Furthermore, organizational management should value knowledge-sharing practices and collaboration among organizational members. According to Yildiz et al. (2024), strengthening a culture that encourages the exchange of ideas and learning from external sources contributes to enhancing employees' absorptive capacity. This process can be fostered through the implementation of cross-functional teams, communities of practice, and structured knowledge management platforms.

The limitations of this study are acknowledged with regard to its scope and reach. Particular attention should be given to the issue of generalizability. This limitation is not solely related to the sample size, but also to the heterogeneity of the sector under analysis. The sample was characterized by differences in terms of products, target markets, firm size, and the origin of the firms.

This study has been confined to a partial understanding of the process of technological capability accumulation, focusing specifically on learning processes. The approach to technological capability is extensive and encompasses additional variables that may be incorporated to complement the analyses and results obtained.

Investigating the macroeconomic, market, and technological implications—such as industrial, science and technology, and educational policies—on the accumulation of technological capabilities is of fundamental importance for a deeper understanding of the subject. Equally important is the expansion of the analysis to encompass organizational dimensions, including adopted strategies, leadership, and technological patterns.

In other words, further research should seek to provide more comprehensive explanations of the process and accumulation of technological capabilities by examining both external and internal elements of organizations.

References

Adam, N. A., & Alofaysan, H. (2023). External knowledge flows and small and medium-sized enterprises' innovation capabilities enhancement: An empirical investigation. *Sustainability*, *15*(5), 1-14. https://doi.org/10.3390/su15054071

Alzate-Alvarado, A. L., Ribes-Giner, G., & Moya-Clemente, I. (2025). Influence of technological capability, management teams and access to finance on sustainable entrepreneurship over time. *International Entrepreneurship and Management Journal*, *21*(89), 1-30. https://doi.org/10.1007/s11365-025-01106-4

Angelidou, S., Mount, M., & Pondza, K. (2022). Exploring the asymmetric complementarity between external knowledge search and management innovation. *Technovation, 115*(2), 1-11. https://ideas.repec.org/a/eee/techno/v115y2022ics0166497222000190.html

Baginski, L., Pitassi, C., & Barbosa, J. G. (2017). Technological capability in the Brazilian naval industry: a metric for offshore support vessels. *RAI Revista de Administração e Inovação,14* (2), 109-118. https://www.sciencedirect.com/science/article/pii/S1809203917300323

Bath, G. D. (2001). Knowledge management in organizations: examining the interaction between technologies, techniques, and people. *Journal of Knowledge Management, 5*(1), 68-75. https://www.emerald.com/insight/content/doi/10.1108/13673270110384419/full/html

Bell, M. & Pavitt, K. (1995). The development of technological capabilities. In I. Haque (Ed.). *Trade, Technology and international competitiveness* (pp. 69-100). World Bank.

Benedito, P., Rochina-Barrachina, M. E., & Sanchis, A. (2014). Learning through experience in Research & Development: An empirical analysis with Spanish firms. *Technological Forecasting and Social Change*, *88*(1), 290-305. https://www.sciencedirect.com/science/article/abs/pii/S0040162513002679.

Cassiolato, J. E. (2004). *Interação, aprendizado e cooperação tecnológica*. (texto preparado para a RICYT – Red Iberoamericana de Indicadores de Ciência y Tecnología). IE/UFRJ

Egbetokun, A. A., Adeniyi, A. A., Siyanbola, W. O., & Olamade, O. O. (2012). The types and intensity of innovation in developing country SMEs: evidences from a Nigerian subsectoral study. *International Journal of Learning and Intellectual Capital, 9*(1-2), 98-112. https://mpra.ub.uni-muenchen.de/35796/

Errico, F., Messeni Petruzzelli, A., Panniello, U., & Scialpi, A. (2024). Source of funding and specialized competences: The impact on the innovative performance of Start-ups. *Journal of Knowledge Management, 28*(2), 564–589. https://doi.org/10.1108/JKM-11-2022-0928.

Field, A. (2013). *Discovering Statistics Using IBM SPSS Statistics* (4th ed.). Sage Publications.

Figueiredo, P. N. (2001). *Technological Learning and Competitive Performance*. Edward Elgar.

Figueiredo, P. N. (2002). Learning processes features and technological capability-accumulation: explaining inter-firm differences. *Technovation*, *22*(11), 685-698. https://www.sciencedirect.com/science/article/pii/S0166497201000682

Figueiredo, P. N. (2003). Learning, capability accumulation and firms' differences: evidence from latecomer steel. *Industrial and Corporate Change, 12*(3), 607–643. https://academic.oup.com/icc/article-abstract/12/3/607/868736

Figueiredo, P. N. (2009). *Gestão da inovação: conceitos, métricas e experiências de empresas no Brasil*. LTC.

Figueiredo, P. N. (2014). Beyond technological catch-up: An empirical investigation of further innovative capability accumulation outcomes in latecomer firms with evidence from Brazil. *Journal of Engineering and Technology Management,13*(1),73-102. https://www.sciencedirect.com/science/article/abs/pii/S0923474813000787

Fuentes-Fernández, R., Sánchez-García, E., Martínez-Falcó, J., & Marco-Lajara, B. (2024). Uncovering external factors that influence the acquisition of knowledge for innovative purposes. *Operational Research*, *24*(3), 1-28. https://doi.org/10.1007/s12351-024-00853-6

García-Sánchez, E., García-Morales, V. J., & Martín-Rojas, R. (2018). Analysis of the influence of the environment, stakeholder integration capability, absorptive capacity, and technological skills on organizational performance through corporate entrepreneurship. *International Entrepreneurship and Management Journal, 14*(2), 345–377. https://link.springer.com/article/10.1007/s11365-017-0436-9

García-Vega, M., & Vicente-Chirivella, O. (2024). The role of public external knowledge for firm innovativeness. *International Journal of Industrial Organization,93*, 1-26. https://doi.org/10.1016/j.ijindorg.2024.103056

Ge, S., & Liu, X. (2022). The role of knowledge creation, absorption and acquisition in determining national competitive advantage. *Technovation, 112*(1), 1-18. https://www.sciencedirect.com/science/article/abs/pii/S0166497221001772

Gertler, M. S. (2003). Tacit knowledge and the economic geography of context, or the undefinable tacitness of being (there). *Journal of Economic Geography, 3*(1), 75-99. https://academic.oup.com/joeg/article-abstract/3/1/75/904624

Hair, J., et al. (2009). *Multivariate Data Analysis*. (17th ed.). Prentice Hall.

Hansen, U. E., & Ockwell, D. (2014). Learning and technological capability building in emerging economies: The case of the biomass power equipment industry in Malaysia. *Technovation, 34*(10), 617-630. https://www.sciencedirect.com/science/article/abs/pii/S0166497214000984

Hou, C., & Nie, Z. (2022). Interplay of External and Internal Knowledge: Business Model Innovation Analysis in Chinese Publicly Traded Film Companies. *Sustainability*, *14*(16), 1-14. https://www.mdpi.com/2071-1050/14/16/10150

Jha, P. P., & Cottam, E. (2021). Embeddedness of Inter-firm Ties and Knowledge Creation. *European Management Review, 18*(1), 215-227. https://onlinelibrary.wiley.com/doi/full/10.1111/emre.12455.

Kim, L. (2001). The dynamics of technological learning in industrialisation. *International Social Science Journal, 53*(168), 297-308. https://onlinelibrary.wiley.com/doi/abs/10.1111/1468-2451.00316

Kogut, B., & Zander, U. (1992). Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Science, 3*(3), 83-397. https://pubsonline.informs.org/doi/10.1287/orsc.3.3.383

Lall, S. (1992). Technological capabilities and industrialization. *World Development, 20*(2), 165–186. http://www.sciencedirect.com/science/article/pii/0305-750X(92)90097-F

Laptev, G., & Shaytan, D. (2023). Knowledge transferring and conversion in the early stage of collaborative product design by entrepreneurial teams. *Measuring Business Excellence, 27*(2), 291-306. https://www.emerald.com/insight/content/doi/10.1108/MBE-02-2022-0028/full/html

Liao, S. H., Wu, C. C., Hu, D. C., & Tsui, K. A. (2010). Relationships between knowledge acquisition, absorptive capacity and innovation capability: an empirical study on Taiwan's financial and manufacturing industries. *Journal of information science*, *36*(1), 19-35. https://doi.org/10.1177/0165551509340

Molina-Domene, M. A., & Pietrobelli, C. (2012). Drivers of technological capabilities in developing countries: An econometric analysis of Argentina, Brazil and Chile. *Structural Change and Economic Dynamics, 23*(4), 504-515. https://www.sciencedirect.com/science/article/abs/pii/S0954349X11000749

Nonaka, I., & Takeuchi, H. (1995). *The knowledge-creating company: How Japanese companies create the dynamics of innovation*. Oxford University Press.

Nonaka, I., Toyama, R., & Konno, N. (2000). SECI, Ba and leadership: a unified model of dynamic knowledge creation. *Long Range Planning,33*(1), 5-34. https://www.sciencedirect.com/science/article/abs/pii/S0024630199001156

Nonaka, I., Toyama, R., & Hirata, T. (2008). *Managing flow: A process theory of the knowledge-based firm.* Palgrave Macmillan.

Olamade, O. O. (2001). *Technological Capabilities in the Nigerian Telecommunications Industry*. [Unpublished M. Sc. dissertation, Technology Planning and Development Unit, Obafemi Awolowo University, Ile-Ife, Nigeria]. Nigeria.

Pinto, H., Guerreiro, J.A., & Fernández-Esquinas, M. (2023) Sources of knowledge in the firm: a review on influential, internal and contextual factors in innovation dynamics. *SN Bus Econ 3*(57), 1-32. https://doi.org/10.1007/s43546-023-00430-7

Prencipe, A., & Tell, F. (2001). Inter-project learning: processes and outcomes of knowledge codification in project-based firms. *Research Policy*, *30*(9), 1373-1394. https://www.sciencedirect.com/science/article/abs/pii/S0048733301001573

Romijn, H. (1997). *Acquisition of Technological Capability in Development: A Quantitative Case Study of Pakistan's Capital Goods Sector*. *World Development, 25*(3), 359-311. https://www.sciencedirect.com/science/article/abs/pii/S0305750X96001155

Sherwood, A. L., & Covin J. G. (2008). Knowledge Acquisition in University–Industry Alliances: An Empirical Investigation from a Learning Theory Perspective. *The Journal of Product Innovation Management, 25*(2), 162–179. https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-5885.2008.00292.x

Tacla, C. L., & Figueiredo, P. N. (2006). The dynamics of technological learning inside the latecomer firm: evidence from the capital goods industry in Brazil. *International Journal of Technology Management*, *36*(1-3), 62-90. http://dx.doi.org/10.1504/IJTM.2006.009962

Teece, D. J. (2007). The role of managers, entrepreneurs and the literati in enterprise performance and economic growth. *International Journal of Technological Learning, Innovation and Development, 1*(1), 43-64. https://doi.org/10.1504/IJTLID.2007.015018

Tu, Q., Vonderembse, M. A., Ragu-Nathan, T. S., & Sharkey, T. W. (2006). Absorptive capacity: enhancing the assimilation of time-based manufacturing practices. *Journal of operations management*, *24*(5), 692-710. https://doi.org/10.1016/j.jom.2005.05.004

Yam, R. C. M., Lo, W., Tang, E. P. Y., & Lau, A. K. W. (2011). Analysis of sources of innovation, technological innovation capabilities, and performance: An empirical study of Hong Kong manufacturing industries. *Research policy,40*(3), 391-402. http://www.sciepub.com/reference/326068

Yildiz, H. E., Murtic, A., Morgulis-Yakushev, S., & Klofsten, M. (2024). Individual-level absorptive capacity: Unveiling the interplay between dispositions and work context. *Technovation*, *131*, 1-15.

Yu, S., & Chen, H. C. (2020). External knowledge, intraorganisational networks and exploratory innovation: an empirical examination. *Innovation: Organization & Management, 22*(3), 250-269. https://www.tandfonline.com/doi/abs/10.1080/14479338.2019.1642764?journalCode=rimp20

Yuen, S. S., & Lam, H. Y. (2024). Enhancing competitiveness through strategic knowledge sharing as a driver of innovation capability and performance. *Sustainability*, *16*(6), 1-19. https://doi.org/10.3390/su16062460

Zahra S. A., Neubaum, D. O., & Larrañeta, B. (2007). Knowledge sharing and technological capabilities: The moderating role of family involvement. *Journal of Business Research*, *60*(10), 1070–1079. https://www.sciencedirect.com/science/article/abs/pii/S0148296307000793.

Zollo, M., & Winter, S. G. (2002). Deliberate Learning and the Evolution of Dynamic Capabilities. *Organization Science*, 13(3), 339–351. https://www.jstor.org/stable/3086025

How to cite:

Nagano, M. S., Iacono, A., & Musetti, T. F. (2025). Analysis of the Acquisition Mechanisms and Conversion of Knowledge to the Technological capacity Accumulation in Brazilian Capital Goods. *Revista Ciências Administrativas, 31*, 1-21. https://doi.org/10.5020/2318-0722.2025.31.e15000

Correspendence address:

Marcelo Seido Nagano
E-mail: drnagano@sc.usp.br.

Antonio Iacono
E-mail: iacono@usp.br

Tiago Fernando Musetti
E-mail: tiagoferm@yahoo.com.br

Received on: *05/06/2024.*
Accepted on: *09/25/2025.*

Appendix A: Questions for measurement of technological capacity

CAPACITY OF PRODUCTION
Functions related to process engineering
i. Acquisition of new equipment
ii. Certifications to improve production
iii. Internal training of production and process techniques
iv. Standardization of activities and processes
v. Productivity monitoring
Functions related to Product Engineering
vi. Product Development Activities vii. Improvement of existing products viii. Investments in the Technological area ix. Introduction of new products in the internal market
Functions related to Quality Engineering
x. Training in quality systems
xi. Treatment of anomalies
xii. Internal Audit
xiii. ISO 9000 Status
xiv. Total Preventive Maintenance Programs
CAPACITY OF LINKS
Functions related to Link Development
i. Joint Actions for PDP ii. Relation with Universities iii. Relationship with customers in the exploration and development of new concepts iv. Development of external contact networks v. Cooperation with regional educational institute vi.

Appendix B: Distribution of the Technological Capacity Index

TCI class	% Companies
0.00-0.10	11.4
0.11-0.20	15.9
0.21-0.30	9.1
0.31-0.40	6.8
0.41-0.50	6.8
0.51-0.60	18.2
0.61-0.70	11.4
0.71-0.80	4.5
0.81-0.90	6.8
0.91-1.00	9.1