On the Convergence-Club Nature of Competitiveness and Efficiency Across Firms by Technological Complexity and Size

Francisco J. Santos-Arteaga, Raquel Marín, Madjid Tavana, and Debora Di Caprio

***Abstract*—Digitalization strategies emerge through interactions among producers, consumers, and institutions across value chains, leading to gains in productivity, the introduction of new patents, and innovations in products and processes. Dynamic capabilities theory extends the static resource-based view of the firm by incorporating learning and innovation in evolving environments. Its collaborative extension has recently been introduced to analyze the behavior of corporate dynamics within evolving ecosystems shaped by information and communication technologies and firms' digitalization strategies. However, empirical evaluations of how digital value chains influence firm-level productivity and innovation remain limited, relying on static efficiency evaluation frameworks. We apply a dynamic slacks-based data envelopment analysis model to a panel of 1369 Spanish manufacturing firms progressing through the emergence and consolidation phases of digitalization that have characterized the early decades of the twenty-first century. We examine how efficiency and competitiveness evolve, finding that larger firms and those in more complex technological sectors show more varied behavior but lower inefficiency. The findings offer implications for theory, best practices, and digitalization policies. The robustness of our analysis has been validated by demonstrating substantial differences between the patterns obtained under the standard static and our dynamic evaluation environments.**

***Managerial Relevance Statement*—Engineering managers can use the findings of this study to recognize that digital transformation yields differentiated efficiency trajectories, depending on firm size and technological complexity. Small and medium-sized firms, particularly those operating in low- and medium-technology sectors, should avoid pursuing digitalization in isolation. Instead, strategic alignment with technologically advanced firms within their value chains can accelerate knowledge absorption, stabilize performance during technological transitions, and reduce persistent inefficiencies. The convergence patterns identified in this study provide a practical benchmark for assessing a firm's relative digital and innovation performance, as well as for supporting phased decision-making on R&D investment, technology adoption, and process upgrading under resource constraints.**

Policy makers can draw on the findings of this study to design more effective and targeted digitalization and innovation policies. The evidence indicates that uniform policy approaches are unlikely to close efficiency gaps across firm groups. Differentiated instruments should therefore reflect the dynamics of the convergence club phenomenon, accounting for firm size and technological content. Targeted measures, including incentives for supply-chain integration, collaborative R&D platforms, and technology transfer partnerships, can accelerate convergence and reduce structural inefficiencies. The dynamic evaluation framework presented in this study also provides a practical and robust mechanism for monitoring the long-term effects of industrial digitalization policies and refining interventions based on observed efficiency trajectories, rather than relying on standard static indicators.

This article also contributes to the following SDGs: SDG 8 and SDG 9.

***Index Terms*—Collaborative dynamic capabilities, convergence clubs, digital value chains, digitalization, dynamic data envelopment analysis.**

I. Introduction

The implementation of emerging digital technologies into industrial processes and their effect across different market sectors have been consistently analyzed in the literature [1], [2]. Information and communication technologies (ICTs) have been used to transform traditional value chains into network systems, further leading to the development of innovation ecosystems and the introduction of new products and services [3], [4]. Applying ICTs to manufacturing firms and their inherent production and distribution processes has intensified firm competition and led to the emergence of Industry 4.0.

The evolution of firms and their capacity to innovate are conditioned by their ability to implement and assimilate digital technologies [5]. That is, the relative level of technological development has conditioned the capacity of Industry 4.0 to enhance the efficiency of the supply and value chains of the adopter firms [6], [7].

Digital technologies have a direct effect on the evolution of value chains and their subsequent influence on the technological

Received 27 November 2024; revised 27 May 2025, 12 September 2025, 25 November 2025, and 19 January 2026; accepted 4 February 2026. Date of publication 16 February 2026; date of current version 6 March 2026. The work of Raquel Marín was supported by the Spanish Ministry of Science and Innovation [Ref: AEI/10.13039/501100011033]. Review of this article was arranged by Department Editor A. Cammarano. *(Corresponding author: Madjid Tavana.)*

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This article has supplementary downloadable material available at https://doi.org/10.1109/TEM.2026.3664073, provided by the authors.

Digital Object Identifier 10.1109/TEM.2026.3664073

innovations introduced by firms through either interaction with customers [8] or modifications in the supply chain [9]. The competition triggered by the process of digital transformation incentivizes firms to introduce new products and processes [10], fostering innovations and the competitive advantage of successful firms [11].

We focus on the effects of digitalization and cooperation through the value chain on firms' productive capacity and ability to innovate. The digital transformation of firms and the subsequent modifications in their organizational structure have fostered the advent of business ecosystems within which innovation processes are developed [12], [13]. Introducing patents and technological innovations in the form of new products or processes confers an important competitive advantage to firms and, as such, defines some of the main potential outcomes derived from digitalization [14]. Digitalization processes are also reinforced as firms internationalize [15].

On the other hand, digitalization processes are constrained by the investment requirements imposed particularly on smaller firms, which must enhance their knowledge acquisition capacities to remain competitive [16]. Cost constraints are compensated by a series of benefits derived from digital technologies, which include logistic and communication improvements enhancing, for instance, the capacity of firms to source knowledge and reduce transaction costs [17].

The standard empirical models within the business and management literature do not generally consider the evolution of firms when implementing a series of technological improvements through time. The introduction of digital technologies within their value chains constitutes a dynamic process and must, therefore, be studied as such.

A. *Dynamic Capabilities Theory and Its Evolution Into Collaborative Dynamic Capabilities*

The intuition motivating the current research builds on the extension defined by the dynamic capabilities theory (DCT) presented in [18] and [19] relative to the static resource-based view of the firm [20]. The latter was not designed to analyze the preservation of competitive advantage in evolving market environments. DCT highlighted the fact that the structural differences conditioning the performance of firms across different market environments go well beyond their unequal endowment of resources and capabilities and are determined by their ability to learn continuously and maintain their competitive advantage in changing market environments [21].

DCT demonstrates how organizations combine and restructure their resources to maintain their competitive quality amidst rapidly evolving industries, highlighting the importance of ongoing learning skills and innovation outcomes. The consistent importance of dynamic capabilities (DC) among industry managers—enhancing our understanding of how firm-level competitive advantage is created and maintained—remains reflected in its current relevance within the management literature [22].

Digitalization processes have a significant effect on the scale and speed of ecosystemic evolution [23], fostering redefinitions of the industry boundaries [24], with manufacturing firms being especially affected by these induced changes [25]. Witschel et al. [26] noted that manufacturing firms generally focus on increasing their efficiency via digital technologies instead of implementing growth-oriented strategies such as business model innovation (BMI) [25]. BMI requires rethinking and transforming the way an organization creates and captures value, defining a strategy that is usually hampered by path dependencies, resource rigidity, and the fear of cannibalization [27].

Zare and Persaud [28] reviewed the literature describing the complementary relationship between digital transformation and BMI, fostered by the implementation of digital technologies across industries and supply chains. The changing conditions of BMI in digitalization environments require DCs from firms to remain competitive [29], exploiting their relationship with innovation and organizational performances [30]. These interconnections have been analyzed by Witschel et al. [31], who applied a microfoundations approach to evaluate the importance of DCs as enablers of digital transformation in a variety of case studies.

These analyses, while essential for the development and validation of a formal theory, do not describe the dynamic interactions across the factors determining the evolution of firms and their convergence processes, which has led to the introduction of a networked strategic version of DCT. That is, DCs display a reciprocal reinforcing relationship with collaborative practices and open innovation [32], with cooperation conditioning the strategic evolution of firms competing in highly technological environments [33]. Collaborative dynamic capabilities (CDCs) were introduced by Kodama [34] to analyze corporate dynamics in changing and evolving environments displaying convergence across industries, particularly those driven by ICTs.

The general-purpose quality of ICTs fosters their implementation across industries, allowing CDCs to focus on convergence through cross-sectoral integration and the development of knowledge assets via strategic communities (SCs). In particular, CDCs nurture co-creation and innovations leading to new business models with SCs acting as platforms to span collaboration across sectorial boundaries within networked environments [35].

CDCs build on the DCs model presented in [18], highlighting the importance assigned to the reciprocal strategies developed within an ecosystem. The theoretical framework developed by CDCs focuses on the changes taking place at the corporate-level in scenarios of cross-sectoral convergence where firms exchange knowledge resources intensively across organizational boundaries to increase the flexibility of their capabilities [36]. CDCs suggest exploiting dissimilar knowledge assets existing across organizational and sectoral boundaries, going beyond the standard approach of DCs [30]. The analyses performed consider mainly large firms, leaving aside the complex dynamics arising across horizontal networks [37].

Jucevičius and Jucevičienė [35] extended the CDCs framework from a firm-centric to a network-centric environment, fostering the synthesis of capabilities and co-specialization across firms and industries within strategic ecosystem communities. Firm-centric SCs develop vertically integrated architectures based on their internal learning processes and interactions with the knowledge and capabilities of external partners. On the other hand, network-centric SCs develop horizontally integrated architectures focused on diversifying their knowledge base and enhancing their absorptive capacities when collaborating across different sectors. As a result, the authors focused on trust building, co-specialization, and capability synthesis as key factors enabling this strategic extension.

All in all, CDCs are designed to integrate different technologies in the development of new products and processes across industries. In this regard, our research serves as an empirical counterpart to the dynamic strategic tendency identified in the literature on managerial and firm capabilities, evaluating whether the dynamic evolution of digital value chains and the subsequent productivity and innovation outcomes validate the main conclusions of CDC theory.

When validating the corresponding theoretical frameworks, the empirical literature on DCs consists mainly of econometric models that lack the capacity to illustrate the evolution of the various cumulative factors that determine the behavior and efficiency of firms as they interact in changing environments triggered by their digitalization processes. The literature on engineering management has extended the findings of econometric models applied by business and economics scholars [38], [39] by shifting the focus to the analysis of efficiency and to the implementation of more flexible data envelopment analysis (DEA)–based hybrid models. This engineering-based approach has several advantages relative to the statistical one, ranging from its nonparametric nature to its ability to simultaneously account for multiple output variables arising from firms' production processes.

However, most of these models assume static environments, substantially limiting the extent and generalizability of their analyses. This limitation applies to a variety of hybrid models combining DEA with evaluation techniques such as reinforcement learning [40] and the analytical hierarchy process [41]. This is also the case when the malleability of DEA is exploited to account for fuzzy evaluation settings [42] or regrettable decisions inherent to the risk faced by decision-makers [43]. DEA models with multiple stages have also been implemented to formalize the sequential nature of production processes [44]. Despite this enhancement, they cannot yet incorporate the dynamic interactions needed to evaluate industry evolution.

B. Contribution

We perform a dynamic analysis of interactions within firms regarding the digital transformation of the value chain and their relationships with the various actors that compose it. These processes develop simultaneously with firms' R&D activities, patent introductions, new products and processes, and their expansion into international markets. At the same time, these latter qualities evolve through the assimilation of knowledge from digitalization and through vertical and institutional interactions along the value chain.

The dynamic slack-based measure data envelopment analysis (SBM-DEA) model implemented in this article explores the effects of different sources of technology and knowledge on the evolution of the innovation outputs characterizing the firms over the period analyzed. We analyze a sample of 1369 manufacturing firms evaluated over the period 2000–2016 and located in Spain, a country with subpar innovation scores operating in a digitally competitive environment [39]. We also define two structural evaluation environments, dividing the sample by the technological complexity of the sector in which firms operate and their relative size.

The results obtained indicate that small firms and those competing in low- and medium-technology sectors exhibit a decreasing inefficiency trend over the period analyzed, whereas large firms and those competing in high-technology sectors display more volatile behavior within a decreasing inefficiency pattern. Firms belonging to the latter groups are consistently more efficient than those within the former ones over the period analyzed.

These results imply that strategic interactions should be fostered both across industries and industrial sectors; that is, firms should not only interact horizontally with members of their clusters but also create alliances and consistently collaborate with vertical competitors. The dynamic behavior of the main factors that determine firms' productivity and innovation outcomes supports the CDC model's intuition, as corporate capabilities that foster strategic collaborations within and across organizations enhance co-evolution among companies, leading to the creation of new business models and value chains [34].

Furthermore, artificial intelligence (AI) defines the same type of dynamic patterns, spreading faster than ICTs and across a wider variety of technologies. Damioli et al. [45] used a global dataset on patenting activities from 2000 to 2016 to suggest that the introduction of AI constitutes a shift in the technological paradigm relative to the one previously defined by digital ICTs. The authors highlight that patenting of AI accelerated and became more pervasive from 2000 to 2016. At the same time, AI innovators shifted from their initial ICT core industries to other non-ICT service sectors. Moreover, there has been a decrease in the concentration of innovation activities, with younger and smaller patent applicants across industries successfully challenging leading ICT incumbents. The general-purpose technology quality of AI has driven innovation and accelerated its introduction.

The findings derived from our model validate these features for digital ICTs over the same period of analysis, namely throughout the emergence and consolidation phases of digitalization up to 2016. More importantly, our results imply that, given the efficiency, productivity, and innovation trajectories observed during this historical period of digitalization, engineering managers and policymakers should consider AI to generate similar, but more widespread and pervasive, patterns across technological sectors and firm sizes. The faster evolution of AI should also encourage them to define and continuously update cross-sectoral strategic operations. If these features were not fully acknowledged, the divergent patterns arising from the implementation of ICTs would be exacerbated, leading to a progressive worsening of the main characteristics that define the performance of the less efficient sectors. These consequences will be illustrated in the discussion of the data evolution presented in Section V.

From a robustness perspective, our analysis highlights biased results arising from the use of a static DEA framework to evaluate firm behavior. The differences between SBM-DEA and the standard DEA approach are presented in the online Appendix A, where we illustrate how the static optimization models used in the literature to assess efficiency on a per-period basis fail to capture the convergence processes identified in a dynamic formalization environment. That is, a static evaluation framework remains insufficient to observe the dynamic interactions among the main variables defining value chains, thereby limiting the ability to observe innovations and the relative efficiency of the corresponding firms.

The following section describes in detail the variables chosen to evaluate the efficiency of firms and their evolution. The variables selected condition firms' innovation incentives, which, at the same time, determine their innovation policies. Section III describes and implements the dynamic SBM-DEA model. Section IV discusses the results. Section V discusses the subsequent managerial and policy implications. Finally, Section VI concludes and suggests potential research extensions.

II. Formal Structure and Analysis

The efficiency evaluation models implemented by the management literature tend to consider static environments [46], lacking a dynamic orientation that would allow us to analyze the evolution of firms, instead of focusing on discrete individual or two-period Malmquist-based events [47]. Including multiple time periods into a DEA framework requires extending static models to account for the dynamic patterns that occur throughout the planning horizon to obtain unbiased efficiency measures [48].

We build on the dynamic SBM-DEA framework presented by Tone and Tsutsui [49] to study the cumulative quality of the efficiency processes governing the behavior of decision-making units (DMUs). These authors expanded the dynamic model presented in [50] using the slacks-based measure setting defined by Tone [51]. SBM-DEA incorporates carryover activities, named links, across periods and utilizes nonradial measures, which do not require inputs and outputs to change proportionally when moving through the efficiency space.

Carry-overs serve as the primary link across different periods and shape the dynamic nature of the production process among DMUs. These variables are included in the analysis to account for the accumulated impact of both positive and negative outcomes stemming from the productive and structural capacities of DMUs [52].

The inclusion of carry-overs linking sequential periods represents the main difference between the dynamic SBM-DEA framework and standard static DEA models. Carry-overs are used to account for the digitalization process of the value chain and the consistency of the vertical and institutional relationships with its different components. At the same time, the evolution of the value chain reflects the structural and technological characteristics of the strategic knowledge acquired and implemented by firms.

A. Variable Definition

The dynamic persistent effects that digitalization has on the innovation output of firms take the form of patents, products, and process innovations. Furthermore, digitalization processes also condition the productivity and export intensity of firms. As a result, two scenarios have been analyzed based on the structural characteristics defining the firms within the corresponding markets.

1) First, firms have been categorized in terms of the level of technological complexity of the market segment within which they compete, being either high, medium, or low.
2) Second, a specific framework has been defined to differentiate SMEs from larger firms. That is, while size constitutes one of the inputs defining the production process of firms, the specific market structure determined by their categorization as large firms or SMEs has also been analyzed.

The evaluation and comparison of the different results obtained over seventeen years summarizes the behavior and evolution of manufacturing firms across various structurally constrained scenarios. Table I presents multiple empirical references describing the relationships between the different input and output variables as well as the structural features defining the market sectors considered.

III. Dynamic Slacks-Based Measure DEA

The dynamic framework analyzed by Tone and Tsutsui [49], described in Fig. 1, presents a model composed of n DMUs $(j = 1, \ldots, n)$ whose inputs and outputs are evaluated through T periods of time $(t = 1, \ldots, T)$. The endowment of DMUs at the time t consists of a set of m inputs $(i = 1, \ldots, m)$ and a series of carryovers or *links* shifted across periods. DMUs use inputs to produce a set of s outputs $(i = 1, \ldots, s)$ per period, while carry-overs account for cumulative outcomes derived from the production process across periods. We denote the inputs used and outputs produced by DMU_j at time t by x_{ijt} $(i = 1, \ldots, m)$ and y_{ijt} $(i = 1, \ldots, s)$, respectively.

Tone and Tsutsui [49] categorized four different types of carry-overs. We consider only those defined as desirable links, z^{good}, which are equivalent to outputs; that is, higher values represent efficient behavior. Three additional types of links could be incorporated into the analysis: undesirable, z^{bad}, which are equivalent to inputs—namely lower values represent efficient behavior; discretionary, which DMUs can decrease or increase freely; and nondiscretionary, over which DMUs do not have any control.

TABLE I
RELATIONSHIPS BETWEEN THE VARIABLES AND STRUCTURAL FEATURES DEFINING THE MARKET SECTORS ANALYZED

Inputs	**Outputs**				
	Productivity	Patents	Product Innovations	Process Innovations	Export intensity
Size	Zheng et al. [53] Kim [54]	Estensoro et al. [55] Müller et al. [16] Masood and Sonntag [56]			Chung et al. [57] World Trade Organization [58]
Age	Du et al. [59] López et al. [60]	Bouncken et al. [61] Balasubramanian and Lee [62] (-)			Forte and Carvalho [63] Johanson and Vahlne [64]
R&D Intensity	Audretsch et al. [65] Audretsch and Belitski [66]	Zhu et al. [67] Hammar and Belarbi [68] Acs and Audretsch [69]			Benfratello et al. [70] Guckenbiehl et al. [71]
Digitalization Links					
Digital Value Chains	Radicic and Petković [72] Gaglio et al. [73] Papadopoulos et al. [74]	Belhadi et al. [75] Luo et al. [76] Hahn [9]			Eller et al. [77] Rachinger et al. [78]
Institutional Cooperation	Freire and Gonçalves [79] Zekhnini et al. [80]	Marín et al. [39] Yang et al. [81] Radicic and Pinto [82]			Krammer et al. [83] Cantwell and Piscitello [84]
Vertical Cooperation	Aubry and Wang [85] Malacina and Teplov [86]	Domnich [87] Fatorachian and Kazemi [88] Pesch et al. [89] Kamble and Gunasekaran [90]			Griffith et al. [91] Reis and Forte [92]
Structural Features					
Technological sector	Bodendorf and Franke [93] Kádárová et al. [94]	Huynh et al. [95] Zhao et al. [96]			Xie and Li [97] Salomon and Shaver [98]
SMEs	Ojha et al. [99] Abou-Foul et al. [100] Radicic and Pugh [101]	Estensoro et al. [55] (-) Alhusen and Bennat [102] (-)			Saratchandra et al. [103] Obradović et al. [104]

Note: A minus sign between parentheses next to a reference describes a negative relationship.

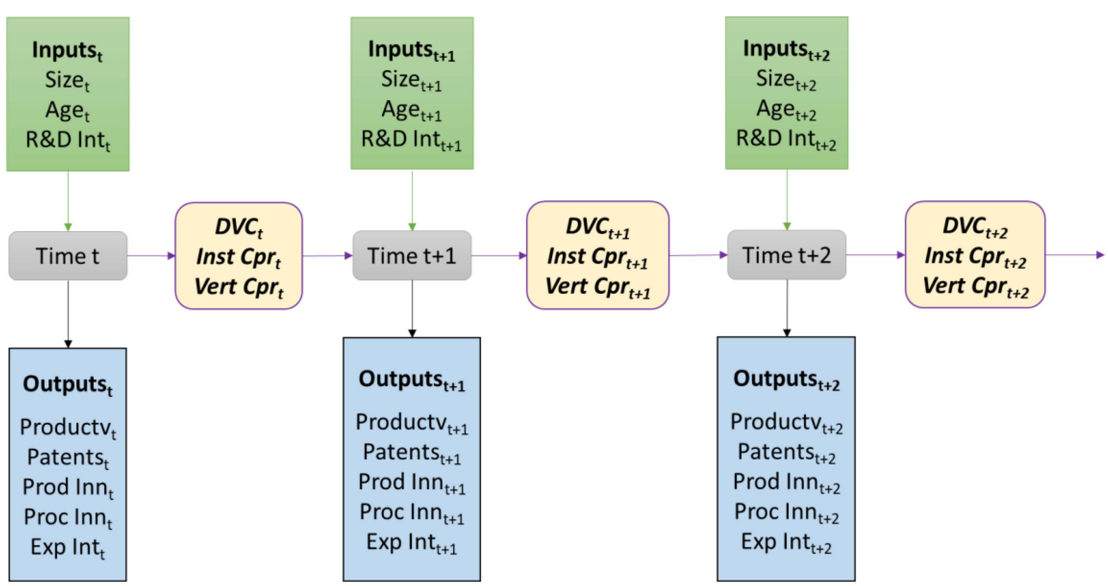

Fig. 1. Implementation of the dynamic framework formalized by Tone and Tsutsui [49].

Given the cumulative nature of technological development and innovation processes, we focus on the desirable aspects inherent to digitalization along the value chain. Carry-overs are defined per period t, item i, and DMU, j, via z_{ijt}^{good} ($i = 1,\ldots,ngood$; $j = 1,\ldots,n$; $t = 1,\ldots,T$), where $ngood$ corresponds to the total number of desirable links. Carry-overs are treated as outputs since improvements in the value chain's digitalization or interactions with its main components constitute desirable outcomes from firms' technological enhancement and growth. Since we analyze the use of resources available and knowledge generated and assimilated by firms as the value chain evolves, we implement an output-oriented framework, which focuses on potential output increments while maintaining input levels constant.

The optimization problem faced by DMU_o ($o = 1,\ldots,n$) is subject to the following set of constraints:

$$x_{iot} = \sum_{j=1}^{n} \lambda_j^t x_{ijt} + s_{it}^- \ (i = 1,\ldots,m;\ t = 1,\ldots,T) \quad (1)$$

$$y_{iot} = \sum_{j=1}^{n} \lambda_j^t y_{ijt} - s_{it}^+ \ (i = 1,\ldots,s;\ t = 1,\ldots,T)$$

$$z_{iot}^{good} = \sum_{j=1}^{n} \lambda_j^t z_{ijt}^{good} - s_{it}^{good} \ \ (i = 1,\ldots,good;\ t = 1,\ldots,T)$$

$$\lambda_j^t \geq 0,\ s_{it}^- \geq 0,\ s_{it}^+ \geq 0,\ s_{it}^{good} \geq 0\ (\forall i,\ t)$$

where $\lambda_j^t \in R^n$ $(t = 1,\ldots,T)$ denotes the intensity vector per period of time, whereas s_{it}^+, s_{it}^-, and s_{it}^{good} define the slack variables corresponding to the outputs, inputs, and desirable links, respectively. Equation (1) could be easily extended to account for desirable and undesirable links, allowing for a direct comparison between both structural settings.

The reliability of the dynamic framework formalized through the optimization problem is preserved across successive periods through the carryover variables. In particular, the consistency of the intensity vectors is upheld across periods by imposing the following set of constraints.

$$\sum_{j=1}^{n} \lambda_j^t z_{ijt}^{good} = \sum_{j=1}^{n} \lambda_j^{t+1} z_{ijt}^{good} \ \ (\forall i;\ t = 1,\ldots,T-1). \quad (2)$$

The subsequent output-oriented problem maximizes the slacks of the outputs and desirable links to derive the overall efficiency of DMU_o ($o = 1,\ldots,n$)

$$\frac{1}{\tau_o^*} = \max \ \ \frac{1}{T}\sum_{t=1}^{T} w^t \left[1 + \frac{1}{s+ngood}\left(\sum_{i=1}^{s}\frac{w_i^+ s_{it}^+}{y_{iot}} + \sum_{i=1}^{ngood}\frac{s_{it}^{good}}{z_{iot}^{good}}\right)\right] \quad (3)$$

subject to the set of constraints described in (1) and (2). The weights assigned to the period of time and the output, w^t and w_i^+, are exogenous and used to highlight the importance of a specific period or output. In this case, the following sets of constraints must be incorporated into the optimization problem

$$\sum_{t=1}^{T} w^t = T \text{ and } \sum_{i=1}^{m} w_i^+ = s. \quad (4)$$

We simplify the presentation by allocating identical unitary values to all the period and output weights via $w^t = 1$ $(\forall t)$ and $w_i^+ = 1$ $(\forall i)$.

The *term efficiency* of DMU_o is defined as follows:

$$\tau_{ot}^* = \frac{1}{1 + \frac{1}{s+ngood}\left(\sum_{i=1}^{s}\frac{w_i^+ s_{iot}^{+*}}{y_{iot}} + \sum_{i=1}^{ngood}\frac{s_{iot}^{good*}}{z_{iot}^{good}}\right)}, \quad (t = 1,\ldots,T) \quad (5)$$

and is determined by the set of optimal values $\{\{\boldsymbol{\lambda}^{t*}\}, \{\mathbf{s}_t^{-*}\}, \{\mathbf{s}_t^{+*}\}, \{\mathbf{s}_t^{good*}\}\}$ obtained from the maximization of (3) constrained by (1) and (2). $\frac{1}{\tau_o^*} \in [0,1]$ denotes the *overall efficiency* of DMU_o, that is, the weighted average of the term efficiencies through the sample period analyzed, $\frac{1}{\tau_o^*} = \frac{1}{T}\sum_{t=1}^{T}\frac{w^t}{\tau_{ot}^*}$.

DMU_o can then be classified as

1) *term t efficient* if $\frac{1}{\tau_{ot}^*} = 1$, i.e., $s_{iot}^{+*} = 0$ $(\forall i)$ and $s_{iot}^{good*} = 0$ $(\forall i)$, at time t;
2) *overall efficient* if $\frac{1}{\tau_{ot}^*} = 1$, i.e., $s_{iot}^{+*} = 0$ $(\forall i, t)$ and $s_{iot}^{good*} = 0$ $(\forall i, t)$.

We assume a constant returns to scale framework; that is, we do not impose the following constraints on the intensity vector variables as part of (1):

$$\sum_{j=1}^{n} \lambda_j^t = 1 \ \ (t = 1,\ldots,T)..$$

The subsequent convex combinations would force firms to focus on targets across the efficiency frontier when defining their objectives. On the other hand, a constant return to scale framework allows firms to focus on specific target firms composing the frontier when designing potential strategies to improve their efficiency.

The dynamic SBM-DEA model allows us to evaluate the evolution of the main variables defining the digitalization strategies of firms across the value chain. The model accounts for the simultaneous interactions between inputs and outputs —as part of the production process—and across the different actors composing the value chain. The efficiency slacks obtained describe the trends displayed by these variables across market sectors categorized in terms of the technological complexity and size of the firms operating within them.

A. Sample Selection

The Survey on Business Strategies (*Encuesta sobre Estrategias Empresariales—ESEE*)[1] collects data periodically on firms from 20 manufacturing industries in Spain. The survey accounts

[1]The authors would like to thank Fundación SEPI for grating us access to the data. The specific questions composing the survey and the methodology applied by the SEPI Foundation to define the different categories based on the answers retrieved can be found at https://www.fundacionsepi.es/investigacion/esee/en/svariables/disponibles.asp.

TABLE II
VARIABLE DEFINITION

Variable	Description
Inputs	
Size	Firm size (number of employees)
Age	Firm age
R&D intensity	R&D expenditure (as a percentage of sales)
Links	
Digital value chain	Firm sales to or purchases from other companies through the Internet (1 yes, 0 no)
Institutional cooperation	Technological cooperation with universities or R&D centers (1 yes, 0 no)
Vertical cooperation	Technological cooperation with customers or suppliers (1 yes, 0 no)
Outputs	
Productivity	Labor productivity (value added by employee, € millions)
Patents granted	Patents granted to the firm (1 yes, 0 no)
Product innovations	Firm introduces new or significantly improved products into the market (1 yes, 0 no)
Process innovations	The firm introduces some significant modifications in the production process (1 yes, 0 no)
Export intensity	Export volume (as a share of sales)
Structural Characteristics of Firms	
Technological sector	High, medium, and low technological content (1 yes, 0 no, per dummy)
SMEs	Small and Medium Enterprises (1 yes, 0 no)

for all firms with more than 200 employees and is representative of firms employing between 10 and 200 workers. In addition to the standard microlevel data describing the productive activities of firms, the survey focuses on their specific technological activities. Starting in 2000, the survey has since incorporated variables to evaluate the effects of digitalization and internet-based digital communication technologies.

We analyze the evolution of digitalization and its effect on firms' innovation output and productivity while considering the level of technological sophistication of the market within which they operate and their size. The variables defining the dynamic SBM-DEA model are described in Table II.

The input variables are standard characteristics considered in the innovation literature as determinants of the technological performance of firms, namely R&D intensity, defined as the percentage of R&D investments over sales, size, defined in terms of the number of employees, and firm age. R&D intensity, age, and size define basic input categories that determine the productivity of firms together with the potential outputs derived from their innovation processes, namely patents and product and process innovations.

Consider now the set of binary links accounting for the intertemporal behavior firms. The digital value chain variable equals one if the firm sells to customers or purchases from suppliers through Internet-based channels requiring electronic data interchange processes. The reliance of firms on external networks is exacerbated by the integration of the different actors composing the value chain via digitalization [105]. The importance of the network determining the outcome of the innovation processes is incorporated through the technological interactions of firms with customers and suppliers via vertical cooperation and with research centers and universities via institutional cooperation. These variables are assigned a value of one if the firm cooperates with the actors composing the value chain and zero otherwise.

The output variables considered include patents, product and process innovations, which constitute the main potential outcomes that may be obtained from firms' innovation processes. Productivity is another standard output variable defined in terms of the value added by an employee. The volume of exports as a share of sales describes the firms' export intensity and accounts for the knowledge exchanged in international markets and the subsequent learning process.

Finally, firms are categorized in terms of the technological content of the sector within which they operate and their size to account for the main structural factors determining their output and innovative activities.

B. Data Requirements Relative to Standard Regression Methods

The entire sample retrieved from the survey consists of 1369 firms, 862 of which are SMEs, whose number of employees ranges between 10 and 250, and 508 large firms, with more than 250 employees, evaluated over the period 2000–2016. Data availability limits the official period of analysis to 2018. Still, the existence of missing values across several variables in the last two years has constrained the analysis to seventeen years.

The nonparametric quality of DEA contrasts with the parametric approach followed by standard regression methods. Besides the absence of an assumed functional form, several significant differences must be highlighted, particularly regarding sample selection. Considered as a panel of data, the sample consists of a series of firms from which observations have been retrieved at some point through the period analyzed.

This analytical approach is not valid in DEA, where observations are required for all the firms' variables over the whole period analyzed, imposing a constraint on the actual number of firms that can be evaluated. For instance, when performing a standard panel data econometric analysis, a total of 1369 firms compose the sample. However, many of these firms lack observations for the whole period analyzed and must therefore be eliminated from the sample when implementing any DEA variant.

Furthermore, firms are eliminated from the sample if they shift category—in terms of technological sector or size—at some point through the period analyzed. The set of firms composing a given sector must be evaluated and compared every period of the sample and must therefore remain consistent through the analysis. Fig. 2 shows a flowchart summarizing the main differences between the structural requirements imposed on the data by econometric models and those of standard DEA and dynamic SBM-DEA frameworks.

To preserve a sufficiently large number of firms, we have maintained those whose category status differs for a unique period. That is, if a firm shifts from a low technological sector

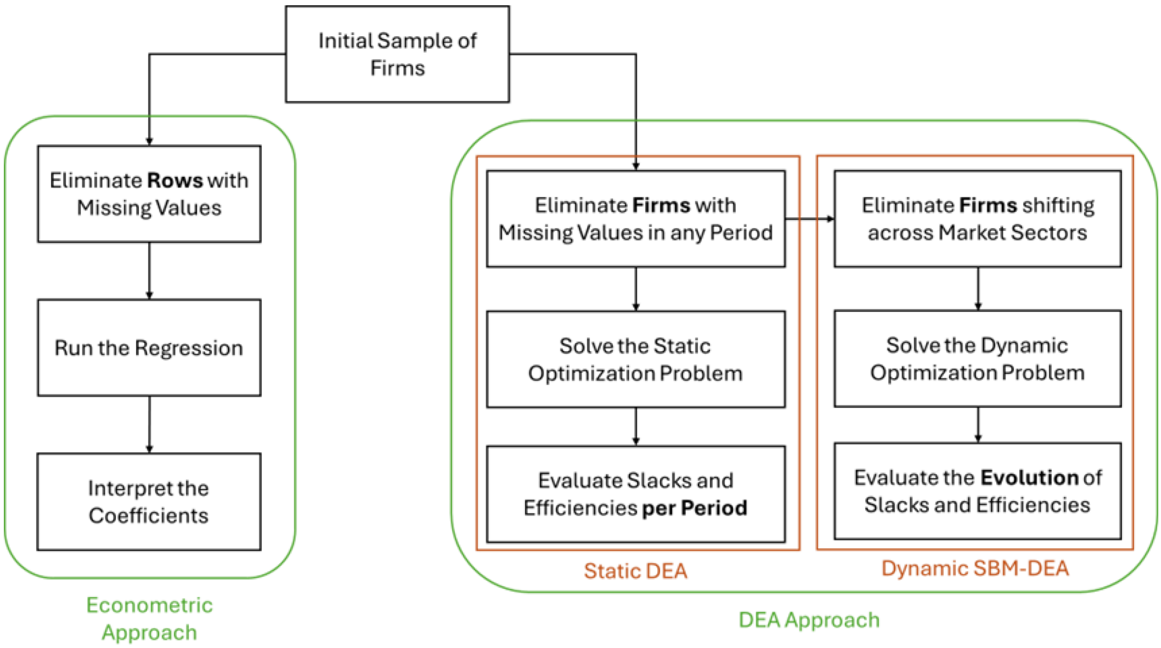

Fig. 2. Structural data requirements: Econometric models, DEA, and dynamic SBM-DEA frameworks.

TABLE III
SAMPLE DISTRIBUTION ACROSS EVALUATION CATEGORIES

	Technological Content (385)			Size (298)	
Category	High	Med	Low	Large	SMEs
Firms	48	156	181	65	233

to a medium one for a unique period, it has been kept in the sample as a low technology firm throughout the whole period of analysis. The firm was eliminated from the sample if the shift occurred for two or more periods. The consistency and homogeneity of the firms have been preserved at the cost of decreasing the size of the samples analyzed. The relative size of the samples and their distribution across categories are both summarized in Table III. For completeness, and to illustrate the consistency of our results, Appendix B presents the results obtained when considering only those firms whose category status has remained unchanged through the entire period of analysis.

We conclude by noting that firms have been distributed across different categories to compare the evolution of their efficiencies relative to that of other firms with similar structural characteristics. That is, focusing on a common sample of firms of different sizes, namely large and SMEs, would bias the results obtained, given the different structural benchmarks imposed by the endowments of the firms within each category.

IV. RESULTS

We illustrate how firms display a consistent coordinated evolution of their digitalization and innovation processes, as well as their interaction strategies throughout the value chain across market scenarios. Figs. 3 and 4 show the dynamic behavior of the average inefficiencies across technological sectors and firm sizes. More precisely, these figures illustrate the evolution of the averages across firms of the outputs' and links' slacks relative to the values of the corresponding variables. Fig. 5 completes the analysis by presenting the percentage of efficient firms and the average efficiency of the firms composing each category within the different scenarios studied. The results obtained are quite heterogeneous regarding slacks, firm efficiency, and their evolution through time, although several patterns can be identified across scenarios.

A. Technological Sophistication of Firms

The first set of scenarios categorizes firms according to the technological content of the industrial sector within which they operate, defined as high, medium, or low. The behavior of the output and link variables across sectors is shown in Fig. 3.

1) *High:* These firms display a substantial variability in the behavior of product and process innovations, which is slightly contained when considering patents. Inefficiencies in productivity decrease consistently over time, whereas the consistency in export intensity should relate to the focus of this group of firms on the international market.
2) *Medium:* Firms operating in this technological sector consolidate their productivity and innovation efficiencies—patents, products, and processes—through time, a pattern

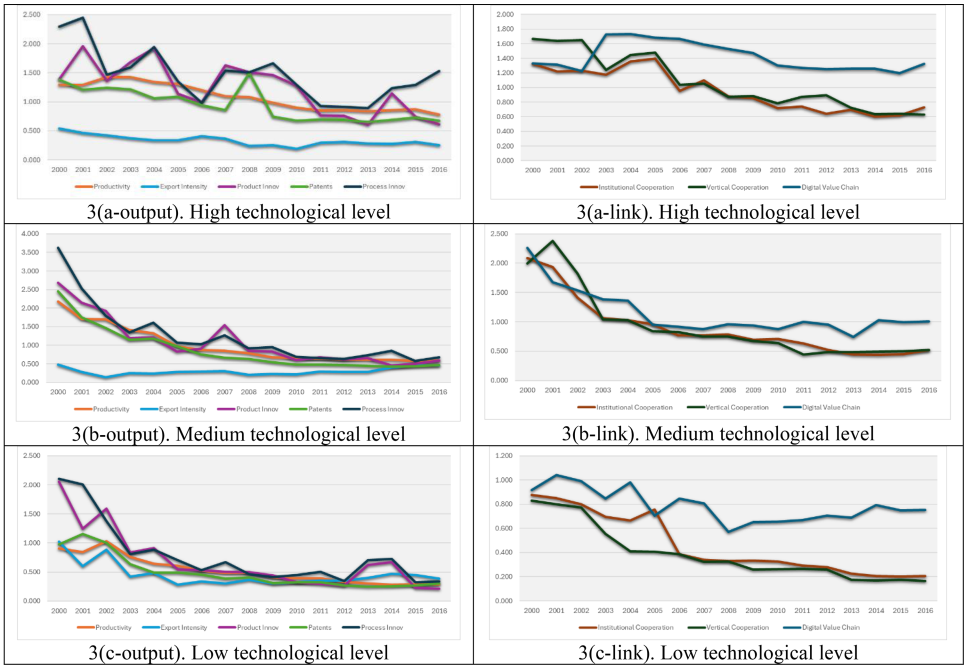

Fig. 3. Output and link inefficiencies and technological sophistication of firms.

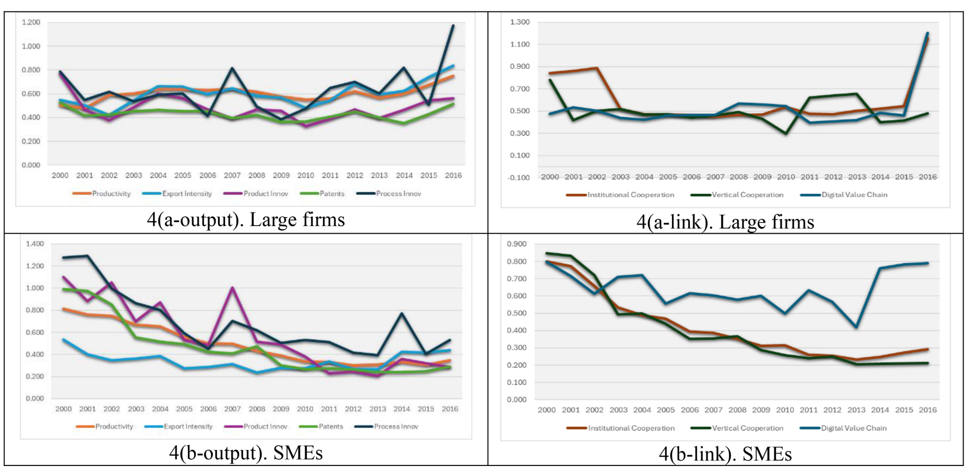

Fig. 4. Output and link inefficiencies and firm size.

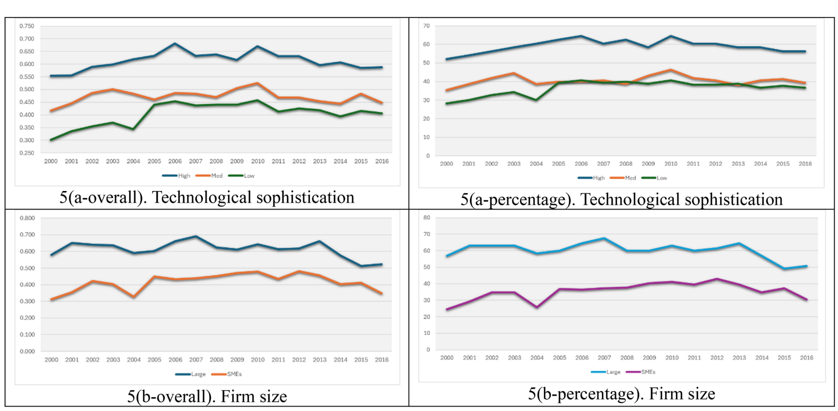

Fig. 5. Overall efficiency and percentage of efficient firms across categories.

coupled with their relatively constant efficiency in export intensity.

3) *Low:* Less technologically sophisticated firms exhibit consistent consolidation patterns in productivity and innovation efficiency—similar to those of the firms composing the medium sector—as well as export intensity.

In all sectors, there is an apparent variability in product and process innovations and, to a lesser extent, patents, which intensifies among firms within the high technological content category. The efficiency in export intensity decreases slightly in the latter years across less technologically sophisticated firms, emphasizing their reliance on domestic markets.

Links display a more homogeneous behavior across market sectors. Firms within all sectors underperform when considering the digitalization of the value chain, whose inefficiency prevails above the others throughout the period analyzed. We also observe a consistent convergence process towards efficiency in institutional and vertical collaborations in all technological sectors. Thus, firms differ in their capacity to implement digitalization within their value chains but have consistently increased their cooperation through the chain in all sectors.

The upper-left panel of Fig. 5 shows the average efficiency of the firms in each sector. We observe that firms in the high-technology sector are consistently more efficient throughout the period analyzed, a feature that persists across sectors as technological sophistication decreases. A concave efficiency pattern is also evident across all sectors, with the least sophisticated firms displaying the largest relative increase through the period analyzed.

B. Firm Size

Firms are categorized by size as either large or SMEs. First, we consider the output variables, which exhibit patterns similar to those observed when distinguishing between high and medium or low technological sectors. Fig. 4 shows the behavior of the output and link variables by firm size, given as follows.

1) *Large:* These firms display substantial variability in process innovations, a quality that is slightly more contained when considering product innovations and patents. Productivity efficiency remains quite stable over time, but decreases in the final periods. An interesting feature is the increase in export intensity inefficiency, which contrasts with the reliance on international markets displayed by firms operating in high-technology sectors.

2) *SMEs:* These firms exhibit a consistent efficiency consolidation pattern throughout the period analyzed, a trend reversed in the latter years in terms of export intensity. Product and process innovations exhibit the greatest volatility in efficiency.

Both types of firms exhibit greater variability in product and process innovations, and the inefficiency of export intensity consistently increases in both cases. However, SMEs exhibit a decreasing inefficiency pattern across most variables, whereas larger firms exhibit an increasing trend.

Links exhibit a fairly consistent behavior across size categories. SMEs underperformed in the digitalization of the value chain, whose inefficiency consistently prevails above that of the other variables. These firms also exhibit a uniform convergence process toward efficiency in institutional and vertical collaboration. Large firms maintained a relatively stable inefficient behavior throughout the period analyzed, lacking the capacity to digitalize their value chains but managing to preserve cooperation over time.

The lower-left panel of Fig. 5 shows the evolution of the average efficiency by size category. The variable follows a concave pattern, with larger firms consistently more efficient within a narrower gap than SMEs.

Overall, small firms and those operating in medium- and low-technology sectors consistently reduce inefficiency throughout the period analyzed. This is the case for both output variables and links – except for export intensity and digital value chains. These firms are less efficient than larger ones, as well as those operating within high-technology sectors. This second group of firms exhibits more heterogeneous behavior in the efficiency of inputs and links, with product and process innovations, as well as digital value chains, displaying the most volatile behavior.

C. Percentage of Efficient Firms Across Categories

As the upper-right panels of Fig. 5 show, the percentage of efficient firms differs substantially across the defined categories. Those competing in high-technology sectors display a higher percentage of efficient firms, a feature that decreases significantly in medium- and low-technology sectors. Firms competing in the low sector managed to close the gap with those in the medium sector, although a substantial difference persists throughout the period relative to the highly sophisticated firms.

A considerable initial difference in efficiency percentages can also be observed between large firms and SMEs. However, the gap decreases in the last years of the sample due to a significant decrease in efficiency among large firms.

Thus, efficiency tends to increase as firms grow and become increasingly competitive. At the same time, the variability in product and process innovations and patents tends to be higher among firms operating in high-technology sectors, which involve intense competition while developing complex innovations. The variability in the efficiency of institutional and vertical collaborations is also higher as firms become more technologically complex and larger. That is, competitiveness fosters heterogeneous collaboration strategies and variable outcomes while enhancing efficiency among firms.

SMEs and firms operating in medium- and low-technology sectors improve their efficiency over time through innovation, patents, and collaborations along the chain. Despite this, their overall efficiency remains consistently below that of large firms and those operating in high-tech sectors. That is, the observed convergent efficiency patterns occur within, not among, market sectors. Countries display a similar behavior when evolving within convergence clubs, a feature consistently analyzed in the economics and business literature [60], [106].

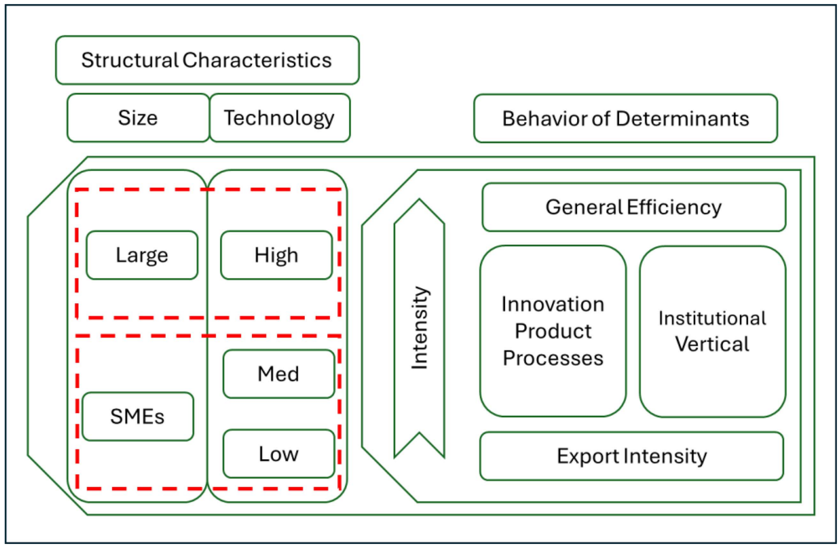

Fig. 6. Structural framework and behavior of the main efficiency determinants within and across market sectors.

Fig. 6 shows the main results of this section, illustrating the behavioral patterns observed among firms within and across market categories. Firms across market sectors have access to similar institutional and digitalization sources but generally differ in their vertical connections and capacity to introduce product and process innovations, develop patents, and operate in the international market. Therefore, best practices and policy recommendations must be defined with these features in mind.

Interactions across market sectors are essential to improve the efficiency of lagging firms, especially SMEs and those competing in less technologically advanced sectors. This important conclusion becomes particularly relevant when comparing the structural recommendations derived from the static and dynamic DEA frameworks. A detailed description of the static evaluation framework is provided in Appendix A, and the outcomes derived from both settings are compared in Fig. A4.

V. Discussion and Strategic Implications

Digital technologies substantially benefit adopting firms, although the size and financial constraints faced by SMEs limit their capacity to adopt [55]. As a result, their ability to source external knowledge constitutes an important determinant of innovation [103]. The implementation of digitalization processes and the strategic cooperation with the different actors composing the chain led to the introduction of technological innovations among firms in Spain during the period 2000-2016, an effect particularly relevant among SMEs [39]. Thus, policies should aim to enhance the creation and stabilization of connections throughout the value chain and provide incentives for firms to foster and implement digitalization processes.

CDCs and SCs are essential to tackling challenges posed by industry convergence, especially when creating interconnected ecosystems in environments that involve diverse actors such as ICT firms and high-tech industries. SCs enhance the ability of firms to access and integrate knowledge across sectoral boundaries through the design of different learning architectures designed by their corporate leaders [35]. Our analysis validates these conclusions while emphasizing the fact that strategic interactions should not remain limited to horizontal cluster environments but extend across technological sectors. Thus, managers of less technologically sophisticated firms and SMEs should aim to establish stable links with their market counterparts, namely larger firms operating in developed technological sectors, to improve their productive and technological assimilation capacities and enhance the subsequent efficiency patterns.

Given the importance of SMEs in the sample analyzed, we now focus on their digitalization, innovation incentives, and potential evolution, based on the results obtained. Throughout the emergence and consolidation phases of digitalization up to 2016, SMEs displayed a consistent pattern of efficiency consolidation through institutional and vertical collaborations while increasingly lacking in export intensity. A similar pattern is observed when examining their productivity and innovation outcomes. On the other hand, these firms underperform in digitalizing their value chains.

Our empirical analysis illustrates how firms converge in efficiency terms within their respective categories through the 2000-2016 period, but convergence does not occur across market categories. That is, the interactions among the factors conditioning convergence have been consistently satisfied by those firms operating within the corresponding sectors, but do not suffice to guarantee convergence across sectors. Larger, technologically advanced firms perform better than their counterparts in the scenarios studied.

The performance of SMEs was positive throughout the period analyzed, but did not suffice to close the efficiency gap relative to larger firms. The structural consequences derived from the divergent quality of the efficiency processes can be observed in the evolution of the variables described in Table IV. Over the 2016–2023 period, SMEs display a consistent lack of linkages and an inability to attract sufficient funding; both features imply

TABLE IV
PERFORMANCE OF INNOVATION SCORES AND LINKAGES AMONG SPANISH SMES

		2016	2017	2018	2019	2020	2021	2022	2023
Digitalisation	EU	100	100	100	100	100	100	108.693	116.637
	Spain	148.199	148.199	148.199	148.199	148.199	148.199	160.789	169.032
Linkages	EU	100	100.962	107.539	111.303	121.11	140.682	146.445	133.39
	Spain	79.767	81.444	98.078	98.218	104.676	122.694	127.231	117.637
Finance and support	EU	100	107.152	106.335	107.621	110.616	114.155	119.537	121.863
	Spain	78.736	91.015	89.865	90.403	90.226	96.442	93.182	98.854
Firm investments	EU	100	100.525	101.049	112.035	112.559	111.373	112.159	108.776
	Spain	54.41	53.886	53.886	56.578	57.627	66.706	68.804	66.338

Sources: Values relative to EU in 2014 = 100. Retrieved from the European Innovation Scoreboard 2023, which is available at https://ec.europa.eu/research-and-innovation/en/statistics/performance-indicators/european-innovation-scoreboard/eis.

a decrease in the efficiency of their production and innovation processes, despite the substantial digitalization efforts observed over these past years.

We must note that the definition of digitalization used to elaborate Table IV differs from ours, extending to the digital abilities of the general population. The European Innovation Scoreboard defines digitalization as the combination of two indicators: broadband penetration among enterprises and the number of people with above-basic overall digital skills. That is, the indicator combines a measure of digital culture with the actual capacity of firms to implement and exploit ICTs. However, the same intuition prevails regarding the capacity of firms to incorporate digital information technologies into their market interactions and production processes.

As highlighted in the introduction section, the results derived from the SBM-DEA model complement and extend those obtained by the econometric literature regarding the main factors determining the behavior of firms [38], [39] and, in this case, their evolution.

VI. CONCLUSION

In this article, we illustrated the evolution of efficiency that resulted from the digitalization process of the value chain among firms located in Spain through the emergence and consolidation phases of digitalization up to 2016, including its effects on the introduction of patents and technological innovations. The knowledge sourced from the digitalization process, together with the vertical cooperation of firms and their institutional links, constituted critical factors determining the development of innovations.

The empirical literature on DCs and innovation consistently highlighted the significant role of R&D activities in developing patents, products, and process innovations. We showed that R&D activities, size, and age enhanced productivity and the output variables differently when considering the technological content of the sectors within which firms operated. From a managerial perspective, our results validated the evolving cumulative quality of business environments identified by CDCs theory, whose strategic collaborative propositions are empirically complemented by our analysis. Thus, future research could categorize firms combining different sets of characteristics to study the effects of digitalization processes or the implementation of AI tools on their strategic interactions across and the evolution of their value chains.

A key formal contribution of the model lay in its robustness. Specifically, we demonstrated substantial differences in the interactions among variables and the subsequent convergence processes when comparing a series of standard static DEA optimization models with the dynamic evaluation framework defined by SBM-DEA.

One of the main drawbacks of implementing DEA models was the loss of observations due to the removal of all firms lacking observations on any of the variables at any point during the evaluation period. As a result, sequential hybrid models consisting of econometric regressions to determine the effects of different factors on efficiency scores were defined in the literature, although they are generally implemented within static DEA environments [107]. The standard technique for evaluating these effects was the Tobit censored regression model, which was a natural choice given the bounded outcomes produced by the different DEA variants. In this regard, the determinants of dynamic efficiency could be analyzed by regressing the scores obtained from the SBM-DEA model on an extended set of independent variables, which constitutes one of the main potential extensions of the current research framework.

Finally, a variety of scenarios could be generated by incorporating additional variables into the analysis, particularly those related to sustainable practices [108], with a focus on the interactions between digitalization and sustainable processes across different business models [109], [110].

REFERENCES

[1] A. Cammarano, V. Varriale, F. Michelino, and M. Caputo, "A framework for investigating the adoption of key technologies: Presentation of the methodology and explorative analysis of emerging practices," *IEEE Trans. Eng. Manage.*, vol. 71, pp. 3843–3866, 2024.

[2] R. Chaudhuri, D. Vrontis, and S. Chatterjee, "Reimaging emerging technologies for digital transformation and growth trajectory of organizations in new normal: The moderating role of organizational data-driven culture," *IEEE Trans. Eng. Manage.*, vol. 71, pp. 13109–13122, 2024.

[3] M. Gebhardt, M. Kopyto, H. Birkel, and E. Hartmann, "Industry 4.0 technologies as enablers of collaboration in circular supply chains: A systematic literature review," *Int. J. Prod. Res.*, vol. 60, pp. 6967–6995, 2022.

[4] B. K. Chae, "A general framework for studying the evolution of the digital innovation ecosystem: The case of big data," *Int. J. Inf. Manage.*, vol. 45, pp. 83–94, 2019.

[5] D. Soto Setzke, T. Riasanow, M. Boehm, and H. Krcmar, "Pathways to digital service innovation: The role of digital transformation strategies in established organizations," *Inf. Syst. Front.*, vol. 25, pp. 1017–1037, 2023.
[6] S. Strazzullo, B. Mignacca, M. Grimaldi, M. Greco, and L. Cricelli, "Industry 4.0 as an enabler of open innovation," *IEEE Trans. Eng. Manage.*, vol. 71, pp. 9388–9401, 2024.
[7] G. I. S. Bolatan, A. Giadedi, and T. U Daim, "Exploring acquiring technologies: Adoption, adaptation, and knowledge management," *IEEE Trans. Eng. Manage.*, vol. 71, pp. 1950–1958, 2024.
[8] G. F. Frederico, J. A. Garza-Reyes, A. Anosike, and V. Kumar, "Supply Chain 4.0: Concepts, maturity and research agenda," *Supply Chain Manage.*, vol. 25, pp. 262–282, 2020.
[9] G. J. Hahn, "Industry 4.0: A supply chain innovation perspective," *Int. J. Prod. Res.*, vol. 58, pp. 1425–1441, 2020.
[10] S. Li, L. Gao, C. Han, B. Gupta, W. Alhalabi, and S. Almakdi, "Exploring the effect of digital transformation on firms' innovation performance," *J. Innov. Knowl.*, vol. 8, 2023, Art. no. 100317.
[11] A. Steiber, S. Alänge, S. Ghosh, and D. Goncalves, "Digital transformation of industrial firms: An innovation diffusion perspective," *Eur. J. Innov. Manage.*, vol. 24, pp. 799–819, 2021.
[12] S. Kraus, S. Durst, J. J. Ferreira, P. Veiga, N. Kailer, and A. Weinmann, "Digital transformation in business and management research: An overview of the current status quo," *Int. J. Inf. Manage.*, vol. 63, 2022, Art. no. 102466.
[13] C. Matt, T. Hess, and A. Benlian, "Digital transformation strategies," *Bus. Inf. Syst. Eng.*, vol. 57, pp. 339–343, 2015.
[14] J. Ross et al., "Designing digital organizations," in *Center Inf. Syst. Res.*, Cambridge, MA, USA, Working Papers, Paper 406, 2016.
[15] W. Chen and F. Kamal, "The impact of information and communication technology adoption on multinational firm boundary decisions," *J. Int. Bus. Stud.*, vol. 47, pp. 563–576, 2016.
[16] J. M. Müller, O. Buliga, and K. I. Voigt, "The role of absorptive capacity and innovation strategy in the design of industry 4.0 business models - A comparison between SMEs and large enterprises," *Eur. Manage. J.*, vol. 39, pp. 333–343, 2021.
[17] P. Grover, A. K. Kar, and Y. K. Dwivedi, "Understanding artificial intelligence adoption in operations management: Insights from the review of academic literature and social media discussions," *Ann. Oper. Res.*, vol. 308, pp. 177–213, 2022.
[18] D. J. Teece, "Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance," *Strategic Manage. J.*, vol. 28, no. 13, pp. 1319–1350, 2007.
[19] G. P. Pisano, "Toward a prescriptive theory of dynamic capabilities: Connecting strategic choice, learning, and competition," *Ind. Corp. Change*, vol. 26, no. 5, pp. 747–762, 2017.
[20] R. L. Priem and J. E. Butler, "Is the resource-based "view" a useful perspective for strategic management research?," *Acad. Manage. Rev.*, vol. 26, pp. 22–40, 2001.
[21] R. Wilden, S. P. Gudergan, B. Nielsen, and I. Lings, "Dynamic capabilities and performance: Strategy, structure and environment," *Long Range Plann.*, vol. 46, no. 1/2, pp. 72–96, 2013.
[22] F. Arndt, P. Galvin, R. J. G. Jansen, G. J. M. Lucas, and P. Su, "Dynamic capabilities: New ideas, microfoundations, and criticism," *J. Manage. Org.*, vol. 28, no. 3, pp. 423–428, 2022.
[23] P. Maijanen, "Digital business ecosystems and dynamic capabilities," in *Handbook on Digital Business Ecosystems*, S. Baumann, Ed. Cheltenham, U.K.: Edward Elgar Publishing, 2022, pp. 50–62.
[24] S. Brenk, D. Lüttgens, K. Diener, and F. Piller, "Learning from failures in business model innovation: Solving decision-making logic conflicts through intrapreneurial effectuation," *J. Bus. Econ.*, vol. 89, pp. 1097–1147, 2019.
[25] J. Björkdahl, "Strategies for digitalization in manufacturing firms," *Calif. Manage. Rev.*, vol. 62, no. 4, pp. 17–36, 2020.
[26] D. Witschel, D. Baumann, and K.-I. Voigt, "How manufacturing firms navigate through stormy waters of digitalization: The role of dynamic capabilities, organizational factors and environmental turbulence for business model innovation," *J. Manage. Org.*, vol. 28, no. 3, pp. 681–714, 2022.
[27] Y. L. Doz and M. Kosonen, "Embedding strategic agility," *Long Range Plann.*, vol. 43, no. 2/3, pp. 370–382, 2010.
[28] J. Zare and A. Persaud, "Digital transformation and business model innovation: A bibliometric analysis of existing research and future perspectives," *Manage. Rev. Q.*, vol. 75, pp. 1999–2032, 2024.
[29] P. J. H. Schoemaker, S. Heaton, and D. J. Teece, "Innovation, dynamic capabilities, and leadership," *Calif. Manage. Rev.*, vol. 61, no. 1, pp. 15–42, 2018.
[30] S. Zhou, A. Zhou, J. Feng, and S. Jiang, "Dynamic capabilities and organizational performance: The mediating role of innovation," *J. Manage. Org.*, vol. 25, no. 5, pp. 731–747, 2019.
[31] D. Witschel, J. M. Müller, and K.-I. Voigt, "What takes the wind out of their sails? A micro-foundational perspective of challenges for building dynamic capabilities towards digital business model innovation," *Schmalenbach J. Bus. Res.*, vol. 75, pp. 345–388, 2023.
[32] M. Bogers, H. Chesbrough, S. Heaton, and D. J. Teece, "Strategic management of open innovation: A dynamic capabilities perspective," *Calif. Manage. Rev.*, vol. 62, no. 1, pp. 77–94, 2019.
[33] F. Saez-Martinez and A. Gonzalez-Moreno, "Strategic renewal, cooperation, and performance: A contingency approach," *J. Manage. Strategy*, vol. 2, no. 4, pp. 43–55, 2011.
[34] M. Kodama, Ed. *Collaborative Dynamic Capabilities For Service Innovation: Creating a new Healthcare Ecosystem*. Cham, Switzerland: Palgrave Macmillan, 2018.
[35] G. Jucevičius and R. Jucevičienė, "Enabling collaborative dynamic capabilities in strategic communities: Firm- vs. network-centric perspectives," *J. Manage. Org.*, vol. 28, no. 3, pp. 587–604, 2022.
[36] G. Schreyögg and M. Kliesch-Eberl, "How dynamic can organizational capabilities be? Towards a dual-process model of capability dynamization," *Strategic Manage. J.*, vol. 28, no. 9, pp. 913–933, 2007.
[37] Y. Chen, L. Liu, W. Li, Z. Xie, and C. Wei, "Microfoundations of dynamic capabilities: A systematic review and a multilevel framework," *Manage. Decis.*, vol. 61, no. 6, pp. 1717–1753, 2023.
[38] N. Omrani, N. Rejeb, A. Maalaoui, M. Dabić, and S. Kraus, "Drivers of digital transformation in SMEs," *IEEE Trans. Eng. Manage.*, vol. 71, pp. 5030–5043, 2024.
[39] R. Marín, F. J. Santos-Arteaga, M. Tavana, and D. Di Caprio, "Value Chain digitalization and technological development as innovation catalysts in small and medium-sized enterprises," *J. Innov. Knowl.*, vol. 8, 2023, Art. no. 100454.
[40] C.-Y. Lee and Y. -W. Chen, "Reinforcement learning with data envelopment analysis and conditional value-At-risk for the capacity expansion problem," *IEEE Trans. Eng. Manage.*, vol. 71, pp. 6469–6480, 2024.
[41] C.-N. Wang, H.-P. Nguyen, and J.-W. Wang, "A two-stage approach of DEA and AHP in selecting optimal wind power plants," *IEEE Trans. Eng. Manage.*, vol. 70, no. 12, pp. 4299–4309, Dec. 2023.
[42] Y. Shao, D. Barnes, and C. Wu, "External R&D supplier evaluation and selection: A three-stage integrated funnel model," *IEEE Trans. Eng. Manage.*, vol. 71, pp. 4101–4115, 2024.
[43] J. Liu, L. Shao, F. Jin, and Z. Tao, "A multi-attribute group decision-making method based on trust relationship and DEA regret cross-efficiency," *IEEE Trans. Eng. Manage.*, vol. 71, pp. 824–836, 2024.
[44] J. Shi, J. Mei, L. Zhu, and Y. Wang, "Estimating the innovation efficiency of the artificial intelligence industry in China based on the three-stage DEA model," *IEEE Trans. Eng. Manage.*, vol. 71, pp. 9217–9228, 2024.
[45] G. Damioli, V. Van Roy, D. Vertesy, and M. Vivarelli, "Is artificial intelligence leading to a new technological paradigm?," *Struct. Change Econ. Dyn.*, vol. 72, pp. 347–359, 2025.
[46] X. Shi, L. Wang, and A. Emrouznejad, "Performance evaluation of Chinese commercial banks by an improved slacks-based DEA model," *Socio-Econ. Plann. Sci.*, vol. 90, 2023, Art. no. 101702.
[47] N. H. Kim, F. He, and O. C. Kwon, "Combining common-weights DEA window with the Malmquist index: A case of China's iron and steel industry," *Socio-Econ. Plann. Sci.*, vol. 87, 2023, Art. no. 101596.
[48] C.-M. Chen, "A network-DEA model with new efficiency measures to incorporate the dynamic effect in production networks," *Eur. J. Oper. Res.*, vol. 194, pp. 687–699, 2009.
[49] K. Tone and M. Tsutsui, "Dynamic DEA: A slacks-based measure approach," *Omega*, vol. 38, pp. 145–156, 2010.
[50] R. Färe and S. Grosskopf, *Intertemporal Production Frontiers: With dynamic DEA*. Norwell, MA, USA: Kluwer, 1996.
[51] K. Tone, "A slacks-based measure of efficiency in data envelopment analysis," *Eur. J. Oper. Res.*, vol. 130, pp. 498–509, 2001.
[52] F. J. Santos-Arteaga, M. Tavana, D. Di Caprio, and M. Toloo, "A dynamic multi-stage slacks-based measure data envelopment analysis model with knowledge accumulation and technological evolution," *Eur. J. Oper. Res.*, vol. 278, pp. 448–462, 2019.
[53] F. Zheng, Y. Li, Z. Jian, and R. Lu, "Industrial productivity dilemma in management and economics: Retrospect and prospect," *Int. J. Manage. Rev.*, vol. 25, pp. 666–686, 2023.
[54] J. Kim, "Innovation failure and firm growth: Dependence on firm size and age," *Technol. Anal. Strategic Manage.*, vol. 34, pp. 166–179, 2022.
[55] M. Estensoro, M. Larrea, J. M. Müller, and E. Sisti, "A resource-based view on SMEs regarding the transition to more sophisticated stages of industry 4.0," *Eur. Manage. J.*, vol. 40, pp. 778–792, 2022.

[56] T. Masood and P. Sonntag, "Industry 4.0: Adoption challenges and benefits for SMEs," *Comput. Ind.*, vol. 121, 2020, Art. no. 103261.

[57] H. F. L. Chung, Z. Ding, and X. Ma, "Organisational learning and export performance of emerging market entrepreneurial firms: The roles of RBV mechanism and decision-making approach," *Eur. J. Marketing*, vol. 53, pp. 257–278. 2019.

[58] World Trade Organization, "World Trade Report 2016: Levelling the trading fields for SMEs," 2016. [Online]. Available: https://www.wto.org/english/res_e/booksp_e/world_trade_report16_e.pdf

[59] J. Du, T. Mickiewicz, and M. Douch, "Individual and institutional ownership, firm age and productivity," *J. Competitiveness*, vol. 13, pp. 23–41, 2021.

[60] S. López, J. Molero, and F. J. Santos Arteaga, "Poverty traps in a frictionless world: The effects of learning and technology assimilation," *Struct. Change Econ. Dyn.*, vol. 22, pp. 106–115, 2011.

[61] R. B. Bouncken, M. Ratzmann, and S. Kraus, "Anti-aging: How innovation is shaped by firm age and mutual knowledge creation in an alliance," *J. Bus. Res.*, vol. 137, pp. 422–429, 2021.

[62] N. Balasubramanian and J. Lee, "Firm age and innovation," *Ind. Corp. Change*, vol. 17, pp. 1019–1047, 2008.

[63] R. P. Forte and S. Carvalho, "Do domestic market characteristics influence firms' export intensity?," *EuroMed J. Bus.*, vol. 19, pp. 398–423, 2024.

[64] J. Johanson and J.-E. Vahlne, "The internationalization process of the firm—A model of knowledge development and increasing foreign market commitments," *J. Int. Bus. Stud.*, vol. 8, pp. 23–32, 1977.

[65] D. B. Audretsch, M. Belitski, and R. Caiazza, "Start-ups, innovation and knowledge spillovers," *J. Technol. Transf.*, vol. 46, pp. 1995–2016, 2021.

[66] D. B. Audretsch and M. Belitski, "The role of R&D and knowledge spillovers in innovation and productivity," *Eur. Econ. Rev.*, vol. 123, 2020, Art. no. 103391.

[67] Z. Y. Zhu, H. M. Xie, and L. Chen, "ICT industry innovation: Knowledge structure and research agenda," *Technol. Forecasting Soc. Change*, vol. 189, 2023, Art. no. 122361.

[68] N. Hammar and Y. Belarbi, "R&D, innovation and productivity relationships: Evidence from threshold panel model," *Int. J. Innov. Stud.*, vol. 5, pp. 113–126, 2021.

[69] Z. J. Acs and D. B. Audretsch, "Innovation in large and small firms: An empirical analysis," *Amer. Econ. Rev.*, vol. 78, pp. 678–690, 1988.

[70] L. Benfratello, A. Bottasso, and C. Piccardo, "R&D and export performance: Exploring heterogeneity along the export intensity distribution," *J. Ind. Bus. Econ.*, vol. 49, pp. 189–232, 2022.

[71] P. Guckenbiehl, G. C. de Zubielqui, and N. Lindsay, "Knowledge and innovation in start-up ventures: A systematic literature review and research agenda," *Technol. Forecasting Soc. Change*, vol. 172, 2021, Art. no. 121026.

[72] D. Radicic and S. Petković, "Impact of digitalization on technological innovations in small and medium-sized enterprises (SMEs)," *Technol. Forecasting Soc. Change*, vol. 191, 2023, Art. no. 122474.

[73] C. Gaglio, E. Kraemer-Mbula, and E. Lorenz, "The effects of digital transformation on innovation and productivity: Firm-level evidence of South African manufacturing micro and small enterprises," *Technol. Forecasting Soc. Change*, vol. 182, 2022, Art. no. 121785.

[74] T. Papadopoulos, S. P. Singh, K. Spanaki, A. Gunasekaran, and R. Dubey, "Towards the next generation of manufacturing: Implications of big data and digitalization in the context of Industry 4.0.," *Prod. Plann. Control*, vol. 33, pp. 101–104, 2022.

[75] A. Belhadi, V. Mani, S. Kamble, S. A. R. Khan, and S. Verma, "Artificial intelligence-driven innovation for enhancing supply chain resilience and performance under the effect of supply chain dynamism: An empirical investigation," *Ann. Oper. Res.*, vol. 333, pp. 627–652, 2024.

[76] S. Luo, N. Yimamu, Y. Li, H. Wu, M. Irfan, and Y. Hao, "Digitalization and sustainable development: How could digital economy development improve green innovation in China?," *Bus. Strategy Environ.*, vol. 32, pp. 1847–1871, 2023.

[77] R. Eller, P. Alford, A. Kallmünzer, and M. Peters, "Antecedents, consequences, and challenges of small and medium-sized enterprise digitalization," *J. Bus. Res.*, vol. 112, pp. 119–127, 2020.

[78] M. Rachinger, R. Rauter, C. Müller, W. Vorraber, and E. Schirgi, "Digitalization and its influence on business model innovation," *J. Manuf. Technol. Manage.*, vol. 30, pp. 1143–1160, 2018.

[79] J. A. F. Freire and E. Gonçalves, "Cooperation in innovative efforts: A systematic literature review," *J. Knowl. Econ.*, vol. 13, pp. 3364–3400, 2022.

[80] K. Zekhnini, A. Cherrafi, I. Bouhaddou, Y. Benghabrit, and J. A. Garza-Reyes, "Supply chain management 4.0: A literature review and research framework," *Benchmarking*, vol. 28, pp. 465–501, 2020.

[81] M. Yang, M. Fu, and Z. Zhang, "The adoption of digital technologies in supply chains: Drivers, process and impact," *Technol. Forecasting Soc. Change*, vol. 169, 2021, Art. no. 120795.

[82] D. Radicic and J. Pinto, "Collaboration with external organizations and technological innovations: Evidence from Spanish manufacturing firms," *Sustainability*, vol. 11, 2019, Art. no. 2479.

[83] S. M. S. Krammer, R. Strange, and A. Lashitew, "The export performance of emerging economy firms: The influence of firm capabilities and institutional environments," *Int. Bus. Rev.*, vol. 27, pp. 218–230, 2018.

[84] J. Cantwell and L. Piscitello, "New competence creation in multinational company subunits: The role of international knowledge," *World Econ.*, vol. 38, pp. 231–254, 2015.

[85] M. Aubry and Y. Wang, "Vertical cooperation stability in R&D programs: A game theory analysis of the semiconductor industry," *Technol. Forecasting Soc. Change*, vol. 209, 2024, Art. no. 123738.

[86] I. Malacina and R. Teplov, "Supply chain innovation research: A bibliometric network analysis and literature review," *Int. J. Prod. Econ.*, vol. 251, 2022, Art. no. 108540.

[87] E. Domnich, "The impact of product and process innovations on productivity: A review of empirical studies," *Foresight STI Gov.*, vol. 16, pp. 68–82, 2022.

[88] H. Fatorachian and H. Kazemi, "Impact of industry 4.0 on supply chain performance," *Prod. Plann. Control*, vol. 32, pp. 63–81, 2021.

[89] R. Pesch, H. Endres, and R. B. Bouncken, "Digital product innovation management: Balancing stability and fluidity through formalization," *J. Prod. Innov. Manage.*, vol. 38, pp. 726–744, 2021.

[90] S. S. Kamble and A. Gunasekaran, "Big data-driven supply chain performance measurement system: A review and framework for implementation," *Int. J. Prod. Res.*, vol. 58, pp. 65–86, 2020.

[91] D. A. Griffith, T. Dean, and G. Yalcinkaya, "Building and leveraging competence exploitation and exploration for firm new product success," *Ind. Marketing Manage.*, vol. 97, pp. 233–244, 2021.

[92] J. Reis and R. Forte, "The impact of industry characteristics on firms' export intensity," *Int. Area Stud. Rev.*, vol. 19, pp. 266–281, 2016.

[93] F. Bodendorf and J. Franke, "The technological transformation process for dynamic capabilities in business operations," *IEEE Trans. Eng. Manage.*, vol. 71, pp. 3671–3687, 2024.

[94] J. Kádárová, L. Lachvajderová, and D. Sukopová, "Impact of digitalization on SME performance of the EU27: Panel data analysis," *Sustainability*, vol. 15, 2023, Art. no. 9973.

[95] T. N. Huynh, P. Van Nguyen, Q. N. Nguyen, and P. U. Dinh, "Technology innovation, technology complexity, and co-creation effects on organizational performance: The role of government influence and co-creation," *J. Open Innov., Technol. Market, Complexity*, vol. 9, 2023, Art. no. 100150.

[96] M. Zhao, F. Wu, and X. Xu, "How does technological complexity affect manufacturers' innovation? Based on the perspective of vertical separation structure," *J. Manuf. Technol. Manage.*, vol. 35, pp. 226–246, 2024.

[97] Z. Xie and J. Li, "Export intensity, domestic competition, and product innovation in an emerging economy," *Int. J. Technol. Manage.*, vol. 74, pp. 96–121, 2017.

[98] R. M. Salomon and J. M. Shaver, "Learning by exporting: New insights from examining firm innovation," *J. Econ. Manage. Strategy*, vol. 14, pp. 431–460, 2005.

[99] D. Ojha, P. C. Patel, and V. Parida, "Virtual integration in SMEs: The digitalization circuitry of dynamic strategic planning for SMEs," *Int. J. Inf. Manage.*, vol. 73, 2023, Art. no. 102657.

[100] M. Abou-Foul, J. L. Ruiz-Alba, and A. Soares, "The impact of digitalization and servitization on the financial performance of a firm: An empirical analysis," *Prod. Plann. Control*, vol. 32, pp. 975–989, 2021.

[101] D. Radicic and G. Pugh, "Performance effects of external search strategies in European small and medium-sized enterprises," *J. Small Bus. Manage.*, vol. 55, pp. 76–114, 2017.

[102] H. Alhusen and T. Bennat, "Combinatorial innovation modes in SMEs: Mechanisms integrating STI processes into DUI mode learning and the role of regional innovation policy," *Eur. Plann. Stud.*, vol. 29, pp. 779–805, 2021.

[103] M. Saratchandra, A. Shrestha, and P. A. Murray, "Building knowledge ambidexterity using cloud computing: Longitudinal case studies of SMEs experiences," *Int. J. Inf. Manage.*, vol. 67, 2022, Art. no. 102551.

[104] T. Obradović, B. Vlačić, and M. Dabić, "Open innovation in the manufacturing industry: A review and research agenda," *Technovation*, vol. 102, 2021, Art. no. 102221.
[105] K. Järvi and S. Kortelainen, "Taking stock of empirical research on business ecosystems: A literature review," *Int. J. Bus. Syst. Res.*, vol. 11, pp. 215–228, 2017.
[106] F. J. Santos-Arteaga, D. Di Caprio, M. Tavana, and A. O'Connor, "Innovation dynamics and labor force restructuring with asymmetrically developed national innovation systems," *Int. Bus. Rev.*, vol. 26, pp. 36–56, 2017.
[107] J. S. Liu, L. Y. Y. Lu, W. M. Lu, and B. J. Lin, "A survey of DEA applications," *Omega*, vol. 41, no. 5, pp. 893–902, 2013.
[108] P. Holzmann and P. Gregori, "The promise of digital technologies for sustainable entrepreneurship: A systematic literature review and research agenda," *Int. J. Inf. Manage.*, vol. 68, 2023, Art. no. 102593.
[109] S. L. Pan, L. Carter, Y. Tim, and M. S. Sandeep, "Digital sustainability, climate change, and information systems solutions: Opportunities for future research," *Int. J. Inf. Manage.*, vol. 63, 2022, Art. no. 102444.
[110] R. Nishant, M. Kennedy, and J. Corbett, "Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda," *Int. J. Inf. Manage.*, vol. 53, 2020, Art. no. 102104.