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Adoption and Optimal Configuration of Smart Products: The Role of Firm Internationalization and Offer Hybridization

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Abstract

Drawing on the digital organization of production leading to Smart Systems, this article analyzes the factors influencing the adoption of product analytic capabilities as well as the optimal smart product capability configuration. In this way, the interplay between smart products, firm internationalization, offer hybridization, and firm performance is examined. By using a unique sample of Spanish industrial SMEs, this study differentiates from previous ones that have mainly used case studies to analyze product smartness. The quantitative analysis yields three contributions. First, it provides rare evidence that the adoption of basic analytic capabilities, i.e. monitoring capabilities, is a relatively frequent activity (about thirty-five percent), whereas the adoption of fully analytic capabilities, i.e. autonomous capabilities, is much less usual (less than ten percent). Second, through binary choice models the study shows direct and mutually reinforcing positive effects of offer hybridization (combined product-service offer) and firm internationalization (foreign production and sales) on the adoption of monitoring capabilities. Third, through the use of a fuzzy-set qualitative comparative analysis (fsQCA) it is demonstrated that monitoring capabilities are necessary and sufficient conditions to obtain superior firm performance. By exploring different sub-samples, other optimal configurations are identified. For instance, fully internationalized firms achieve superior performance by implementing autonomous capabilities.

Keywords: Smart products, monitoring capabilities, autonomous solutions, servitization, SMEs.

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1. Introduction

Digital technologies are a key aspect of advances made in organizing production, and their adoption is widespread across businesses (Kohtamäki et al., 2019; Parida, Sjödin, & Reim, 2019). In the European Union (EU-28), the business dimension of the Digital Adoption Index (DAI)[1] equals 0.82 and grows at an annual rate of 1.5% (World Bank, 2016). The adoption of digital technologies not only enables reduction of production and operational costs, it also adds new product functionalities that transcend traditional product boundaries. Organizations are increasingly offering smart and connected products that can provide autonomous solutions to their users (Porter & Heppelmann, 2014, 2015). Previous studies have typically analyzed the use of smart and connected products through case studies of mostly large corporations (Coreynen, Matthyssens, & Van Bockhaven, 2017; Grubic & Jennions, 2018; Iansiti & Lakhani, 2014; Sjödin et al., 2020); however, the literature lacks survey studies evaluating their adoption rate, antecedents and performance implications within small and medium enterprises (SMEs) (Raff, Wentzel, & Obwegeser, 2020). The present study aims at filling this research gap for a sample of Spanish industrial SMEs that declare to simultaneously operate in manufacturing and technological industries.

The standard framework for connected and smart products presents a nested classification depending on the product's degree of analytic capabilities.[2] This classification progresses through a sequence of monitoring, control, optimization, and autonomous capabilities (Porter & Heppelmann, 2014). We argue that an in-depth empirical investigation of this framework requires examining two separate research questions. First, it is imperative to explore firms' adoption of basic analytic capabilities, i.e. monitoring capabilities, as it is the source of real-time raw data (Grubic & Jennions, 2018; Iansiti & Lakhani, 2014). Hence we seek to analyze selection factors that differentiate firms depending on their use of remote monitoring systems: i.e. the use of sensors to connect with either users, other products and/or the environment as the base to generate the analytic capabilities behind smart products. Secondly, whilst product smartness is built on problem-processing algorithms that identify and predict quality deficiencies, diagnose problems, and estimate solutions (Kahle et al., 2020), its implications for

[1] The DAI business dimension is the simple average of four normalized indicators: the percentage of businesses with websites, the number of secure servers, download speed, and 3G coverage. The index has a minimum of 0 and a maximum of 1.
[2] Analytic capabilities are defined as those specific capabilities "to aggregate, analyze, and use data to make informed decisions that lead to action" (Davenport et al., 2001, p. 117).

firm performance remain unclear. Therefore, the present study aims to uncover the optimal configurations of product analytic capabilities for industrial SMEs.

Another important feature of the present study is to examine other current trends in business strategy in parallel with product strategy. First, we look into the degree of firm internationalization. We argue that internationalized firms are more prone to adopt remote monitoring technology because product connectivity reduce the coordination costs of dispersed geographical networks of distribution and production (Alcácer, Cantwell, & Piscitello, 2016; Chen & Kamal, 2016; Dachs, Kinkel, & Jäger, 2019). Second, we also look into business hybridization of firms offering products and services combined into more comprehensive and innovative market packages (Ulaga & Reinartz, 2011). Drawing on digital servitization literature (Coreynen et al., 2017; Gebauer et al., 2020; Vendrell-Herrero et al., 2017), we argue that hybridization is a forebear of remote monitoring technology since by deploying digital analytic capabilities hybrid firms can better manage the complexities associated with the combined offer of products and services (Kohtamäki et al., 2020). Based on this interplay, we argue that firm hybridization positively moderates the relationship between firm internationalization and the adoption of remote monitoring technology. Hence, we expect internationalized firms to be more inclined to adopt product connectedness technologies when they need to manage a combined global offer/production of products and services.

After outlining the antecedents of product connectedness, we analyze the product analytic capabilities configurations that provide most profits and productivity. This study argues that the use of monitoring capabilities is a necessary and sufficient condition for achieving optimal performance in current business environments, and that greater degrees of product analytic capabilities apply only to certain types of firms (e.g., internationalized and hybrid systems suppliers). Our empirical approach uses a novel non-parametric method to study the decisional outcome trajectories, i.e., fuzzy-set qualitative comparative analysis (fsQCA). The methodological approach selected (fsQCA) is an appropriate comparative method for determining the configurations that generate superior outcomes (Greckhamer et al., 2018; Toth, Henneberg, & Naude, 2017), and works particularly well for testing predictive validity in nested combinatory conditions (Schneider & Rohlfing, 2016).

This study makes three important contributions. First, it responds to recent calls for studies to quantitatively assess the implementation of autonomous solutions (Kohtamäki et al., 2019;

Parida et al., 2019). Second, by doing this, the present study sheds new light on the ongoing autonomous solutions debate by providing evidence of the rate of adoption of connected and smart products amongst industrial SMEs. This is a contextual setting that has been underexplored in the smart products literature (Raff et al., 2020). Lastly, the study breaks new grounds by analyzing firm hybridization and internationalization as factors explaining adoption and performance of smart products, providing new insights for future research endeavors. The implications from these results stand to inform managers and policymakers alike.

2. Theoretical framework and Hypotheses development

2.1. Smart systems and product analytic capability-generation

In this section we start by displaying a baseline framework that explains how smart systems and product analytical generation are formed. As exhibited in Figure 1, smart systems are formed by a number of multi-level nested technological systems that make use of different modules and/or technologies to create four developmental stages of product capabilities (Porter & Heppelmann, 2014, 2015).

[Insert Figure 1]

At the first level we have the information systems that provide valuable information on the operation of the organization, including inventory and product life cycle management. These systems contain four widely used modules in the manufacturing industry; such as, Customer Relationship Management (CRM), Enterprise Resource Planning (ERP), Manufacturing Execution Systems (MES), and Product Lifecycle Management (PLM). Information systems by themselves do not add analytic capabilities to products, but builds historical data that can be transferred via Cloud-based data centers that constitute the core and platform for subsequent systems in developing product analytic capabilities.

In the second level, we have Real-time monitoring systems that use sensors to monitor product location and performance enabling active connectivity between suppliers, users and the product itself (Grubic, 2014). The monitoring developmental stage enables products to operate the Cloud-based centers responsible for data transmission and decision support. Real-time monitoring systems also support the Control stages which incorporates both product operating conditions and predictive service indicators; allowing control through algorithms (Grubic &

Jennions, 2018). An algorithm basically sets rules for a sequence of operations to follow if product conditions change, using simulations to evaluate system performance. Accordingly, system functions that are carried-out through product embedded software can be automatically validated, allowing to control the correct functioning of the product. Data from real-time monitoring and control system is constantly updated in the cloud system. Real-time monitoring system enable a richer interaction between suppliers and users (Kamp & Parry, 2017).

Once combined to the historical data, the information is subsequently submitted to the problem-processing system, the third level. The problem-processing system identifies and predicts emerging problems while recommending optimized solutions. By doing this, products achieve two important analytical capabilities: optimization and autonomy. Optimization involves the use of diagnostic and prognostic algorithm-based analysis to anticipate possible changes in product performance. This predictive information enables products to develop the capacity to take autonomous decision-making processes. Autonomous capacity is especially important in environments in which humans have accessibility difficulties (e.g. mining, oceans, space) or in situations in which conditions can change faster than allow human cognitive capacities (e.g. driving) (Raff et al., 2020).

Together, these systems form the fourth and final level, smart systems. These systems are the bases for generating a complete set of products' analytic capabilities (Kahle et al., 2020). Therefore, smart systems have enabled sensing, monitoring, communicating, processing, controlling, predicting and optimizing analytic capabilities as core elements of smart products. Porter and Heppelmann (2014) argue that Monitoring, Control, Optimization, and Autonomy stages follow a process where subsequent analytic capabilities are developed by embedding these features into the goods produced. Product analytical capabilities enable firms to transcend industrial boundaries and their activity can be crossed over multiple industries. Such firms can have a primary activity in manufacturing and a secondary in technological industries, but the reverse would also be consistent with the formation of smart systems and product analytical capabilities.

2.2. Adoption of remote monitoring technology

The objective of this section is to uncover the factors that make firms add sensors to upgrade from an information system to a real time monitoring system (as per Figure 1). By using sensors, firms can leverage the use of remote monitoring technologies, involving real-time monitoring and field-data collection on product performance and usage (Grubic, 2014). Whilst sensor technology is more than two decades old, its adoption is now surging as it enables the implementation of increasingly popular pay-per-use business models (Grubic & Jennions, 2018). As the main attribute of connected products, remote monitoring technology sustains the development of smart product features such as control, diagnostic and prognostic algorithms that optimizes product use, and can leverage a product's autonomy capability (Porter & Heppelmann, 2014). Given the relevance of connected products, in this section, we seek to elaborate theoretical arguments on how business internationalization and offer hybridization affect the likelihood of adopting remote monitoring technology.[3]

There is growing interest for analyzing the interrelationships between international business and smart technologies (Chen & Kamal, 2016; Dachs et al., 2019). We already know that improvements in ICT enable operative cost reduction of offshore services (Alcácer et al., 2016). Similarly, delivery costs of knowledge intensive services are now practically the same domestically as overseas (Davies, 2004). Following the same intuition, we argue that sensor-rich environments may contribute to significantly reducing the cost of coordination with overseas subsidiaries (production) and intermediaries (distribution).

Remote monitoring technologies offer efficiency-improvement opportunities for the management of fragmented production systems and segmented global consumer base. Sensors provide opportunities for knowing in real time the exact location of products as well as product performance and usage. Morrison, Bouquet, and Beck (2004) provide an example of how firms can successfully extract value from monitoring product usage. *Colorful Paints Worldwide* spun off factories out of the U.S., but introduced sensors at all foreign factories to monitor quality standards and maintain brand reputation. They did the same in random customer locations to monitor product use and consumer satisfaction. Without remote monitoring technology, it would have been impossible to successfully meet the complexities of monitoring product usage globally (Martins, Goméz, & Vaillant, 2015). Similarly, the use of real-time monitoring enables exporting firms to establish a more secure commercial relationship with overseas distributor, making export markets less complex and potentially more attractive (Ju et al., 2011).

[3] Whilst in this paragraph we acknowledge some differences between remote monitoring technology, the use of sensors, and connected products, we consider that these concepts are interchangeable in the context of this study. They will be used as synonyms from this point onwards.

So far, without ignoring the fact that sensors can be beneficial to most firms, the arguments provided seem to suggest that international firms have a higher economic incentive to implement them as they enable a reduction in monitoring and coordination costs with subsidiaries, foreign affiliates and foreign distributors. Based on this, we hypothesize that the degree of firm internationalization is positively related to the adoption of remote monitoring technologies:

Hypothesis 1: Firms with more international presence have a higher likelihood of implementing connected products.

The distinction between the production of goods and services is increasingly blurred. This trend is referred to as business hybridization. Hybrid firms combine products and services into holistic value packages (Ulaga & Reinartz, 2011). On the positive side, hybridization generates a source of business differentiation and offering integratedness that helps to lock-in customers (Vandrell-Herrero, Bustinza, & Vaillant, 2021). But on the negative side, hybrid firms need to implement more complex business-models (Alberti & Varon Garrido, 2017; Bustinza et al., 2018).

We can use the digital servitization framework to analyze the behavior of hybrid companies (Vendrell-Herrero et al., 2017). As its name indicates, digital servitization is explained by service-augmented products that make an extensive use of digital technologies to improve distribution, use and product performance (smart products) (Coreynen et al., 2017). Industrial companies use digital technologies to relaunch their products-services offer. This phenomenon occurs both in product-centric companies as well as in service-centric (Gebauer et al., 2020).

The digital servitization framework advocates that digital technologies and hybrid offers mutually reinforce each other, generating synergetic value for the company (Cenamor, Sjödin, & Parida, 2017; Kohtamäki et al., 2020). The underlying effect of this framework is that the adoption of smart features such as sensors-rich cloud-based systems will enhance the value of the combined product-service offer (Rymaszewska et al., 2017).

Consistent with the digital servitization framework, we argue that remote monitoring technology provides hybrid firms a mechanism for overcoming complexities associated with the joint delivery of products and services. In particular, by deploying digital analytic capabilities, hybrid firms increase connectedness between producer and user, a key feature to achieve business-model sustainability (Sjödin et al., 2020). Accordingly, we hypothesize that hybrid firms are more prone to adopt remote monitoring technologies than non-hybrid firms:

Hypothesis 2: Hybrid firms have a higher likelihood of implementing connected products than non-hybrid firms.

Until now, we have independently analyzed the capacity of sensors to overcome the complexities of internationalization and hybridization. However, there are reasons to believe that there are mutually reinforcing elements that make hybrid firms that internationalize even more inclined to adopt remote monitoring technologies. The research on hybrid firms that internationalize is scarce, but existing evidence seems to indicate that business hybridization and firm internationalization are highly correlated. Previous research points out that hybrid firms have more export intensity than non-hybrid ones (Aquilante & Vendrell-Herrero, 2019). This correlation is found amongst bi-exporters, i.e. firms that export both products and services; which account for only 10% of exporting firms, but represent 30% of worldwide exports sales (Ariu, 2016). One strength of bi-exporting firms is the exploitation of demand complementarities (Ariu, Mayneris, & Parenti, 2020). This capacity to satisfy heterogeneous demands is also applicable to hybrid firms that produce and deliver globally (Parida et al., 2015).

Based on current evidence, we argue that in order to better uphold competitive advantage, internationalized hybrid firms should establish networks that connect businesses, equipment and products (Alcacer et al., 2016). In this way, sensors can be seen as an emerging technology that provide the opportunity to enhance operations of hybrid firms in globally fragmented production and sales (Rezk, Srai, & Williamson, 2016). These synergies between internationalization and hybridization also have consequences in the adoption of sensors because remote monitoring technology enables the joint management of the complexities associated with internationalization and hybridization (Grubic, 2014). Based on this argument, we hypothesize that hybrid firms that are internationalized are the most likely group of firms to adopt remote monitoring technology:

Hypothesis 3: Firm hybridization positively moderates the relationship between firm internationalization and connected products implementation.

2.3. Optimal configurational approaches for smart products

In the previous section, we explored the factors explaining the adoption of connected products. The objective of this section is to theoretically examine the implications of smart products implementation on performance. In doing so, we analyze the association between the degree of product analytic capabilities and firm performance. In particular, we seek to identify the necessary and sufficient conditions that explain superior economic and financial performance, which will be derive into three additional hypotheses.

The smart and connected product framework (Porter & Heppelmann, 2014) considers that analytic capabilities can be divided into stages that generate increasing levels of product smartness: monitoring (real time data availability), control and optimization (algorithm-based analysis) and autonomous solutions (decision-making). We argue that, in the context of Smart systems, the main source of competitive advantage is access to real time data (Porter & Heppelmann, 2015). Following Iansiti and Lakhani (2014), the adoption of data analytics is currently the main source of value for firms as it enables competitive advantage generation from advanced information and knowledge management.

Access of real time data is transforming business-to-business (Opresnik & Taisch, 2015) and business-to-consumer marketing strategies (Erevelles, Fukawa, & Swayne, 2016). As a result, more effective new product features and capabilities can be developed from better understanding customers behavior. There are various ways of making use of data, which means that it is important to build cross-functional analytic capabilities, i.e. Statistics, algorithms, machine learning and business domain knowledge. Previous studies have found that firms with more data quality and quantity availability will make more efficient decisions (Ghasemaghaei, Ebrahimi, & Hassanein, 2018). This means that a necessary condition to achieve superior performance is access to real time data.

Predictive and prognostic algorithms provide valuable indications on how to make product maintenance more efficient. However, under general conditions, the use of algorithms may not be necessary to build a sustainable competitive advantage since algorithm is a single data analytic capability that needs to be implemented in coordination with other analytic capabilities. Overall, data-driven cloud systems are consolidated as the basis of product development strategy. Hence, new sources of competitive advantage may arise from the data availability provided by real time monitoring. Therefore, we pose that:

Hypothesis 4: Monitoring is a necessary and sufficient condition to achieve superior performance

The necessary and sufficient conditions for an optimal configuration, however, may differ for specific groups of firms; namely, hybrid and fully internationalized firms. As defined above, hybrid firms are characterized as firms that sell bundles of products and services. As for fully internationalized firms, they are defined as companies that simultaneously sell and produce abroad.

Whereas the interaction between manufacturing and data-driven cloud systems is a consolidated tool for optimizing product processes and assuring control mechanisms, those manufacturers offering both products and services need to generate the additional analytic capabilities required to effectively deal with service provision (Kahle et al., 2020). Additionally, algorithm-based information can provide valuable insights to product users, and can therefore be commercialized as a service that forms part of a hybrid offer (Kohtamäki et al., 2020; Ulaga & Reinartz, 2011). The digital servitization literature illustrates well this argument (Rabetino et al., 2018). In a large number of cases, the services offered to industrial users of the product not only contain real-time data, but algorithmic predictions are also offered. Good examples of algorithm-based services can be found within the road transport (Ziaee Bigdeli et al., 2018) and industrial equipment industries (Visnjic, Neely, & Jovanovic, 2018). In these industries, the users of trucks and machinery can benefit from a smarter and more efficient product use. The decrease in maintenance costs associated with these services represents an important value-added that may contribute to boosting the performance of original equipment manufacturers. This means that a necessary and sufficient condition to achieve superior performance in hybrid firms is to put in place control and optimization systems. Based on this argument we state:

Hypothesis 5: In hybrid firms, algorithm-based capability is a necessary and sufficient condition to achieve superior performance.

As discussed above, operating in multiple countries increases the coordination and distribution costs, making the use of monitoring technologies more relevant (Alcácer et al., 2016; Chen & Kamal, 2016; Dachs et al., 2019). Moreover, fully internationalized firms may have enough routine-tasks in various countries to make the inclusion of autonomous analytic capabilities worth it.

A sector with a high degree of routine tasks is equipment machinery building for mining purposes. The case of *Joy Global* shows us that the firms producing mining extraction machinery can achieve greater performance by incorporating autonomous solutions in their machinery (see Porter & Heppelmann, 2014). The *Joy Global* case illustrates how autonomous solutions are beneficial for the management of machinery introduced in locations that are difficult to access and perform routine tasks. However, the benefit of the implementation of these technologies goes beyond safety and efficiency improvements of machinery. From the exchange of real time data by different machines operating in geographically distant locations, the company can achieve a rapid learning process on a global scale, something that would be restricted at the local level for domestic companies. Similarly, *Joy Global* can know the problems associated with drilling certain types of sediment in real time, which can allow machinery adjustments when drilling similar sediments in different areas of the planet.

Another competitive advantage of autonomous solutions for firms that already operate in multiple locations is the establishment of barriers to entry. In this sense, Safdar and Gevelt (2019) describe the example of equipment machinery building for agricultural purposes. Domestic companies may have difficulties competing with firms that have previously implemented these technologies in other locations, having thus developed international customer embeddedness and offering integratedness (Vendrell-Herrero et al., 2021). This effect may raise the global market-share of fully internationalized firms.

As a final element, note that the arguments provided are consistent with case studies described in the literature. In most case studies, internationalized firms, contrary to domestic companies, are presented as the ones that can most benefit from implementation of autonomous solutions.[4] Overall, we propose that, for fully internationalized firms, a necessary and sufficient condition to achieve superior performance is to have autonomous systems in place:

Hypothesis 6: In fully internationalized SMEs, Autonomy is a necessary and sufficient condition to achieve superior performance.

Figure 2 exhibits the proposed framework in order to better visualize the predicted interrelationships captured in the study's hypotheses.

[Insert Figure 2]

[4] If we take as a reference the article from Porter and Heppelmann (2014). All case studies identify the implementation of autonomous solutions in fully internationalized firms, e.g. Sonos, Tesla, Babolat, Joy Global, Phillips, Ralph Lauren and Medtronic.

3. Data and Method

3.1. Database

Previous studies have analyzed smart products in the context of large corporations, but not for SMEs (Raff et al., 2020). This study fills this gap by uncovering contemporary trends of product capability adoption within Spanish industrial SMEs. Spain is a relevant context for examining SMEs since Spanish firm demographics show a very small presence of large corporations relative to other business environments, and therefore, technological adoption happens mostly in SMEs (Jin, García, & Salomon, 2019). Regarding firm size and location, we constrained our population to Spanish firms with less than 250 employees.

As discussed above, the study applies to industrial firms that possess production and analytic capabilities. To detect a group of relevant industrial firms operating in production and analytic industries, we used the ORBIS database, a service of Bureau Van Dijk (BvD) (https://orbis.bvdinfo.com). This database provides information of secondary sectors, so it is possible to identify firms that *a priori* combine manufacturing and technological activities. This empirical strategy has been exploited by previous studies (e.g. Opazo, Vendrell-Herrero, & Bustinza, 2018). To construct the population of interest, we followed a two-stage approach. First, we selected the industries of interest. As manufacturing industries, we included NAICS-32 (non-mineral manufacturing including wood, petroleum, plastics and chemical processes, as well as the pharmaceutical industry) and NAICS-33 (mineral manufacturing, including the construction of hardware, vehicles, machines, turbines, and engines). As technological sectors, we considered firms operating in NAICS-54 (Scientific, and Technical Services).[5]

Secondly, we did two independent searches contingent on the distribution of primary and secondary industries. We narrowed down the search by imposing that firms with first industry in manufacturing (NAICS-32 & 33) need to have a secondary industry in scientific and technical services (NAICS-54), and vice versa. This search yielded contact information for 1,020 firms. To proceed with survey implementation, we worked in collaboration with a market research company. Table 1 presents sampling and survey technical specification.

[Insert Tables 1]

[5] The official definition of NAICS-54 is Professional, Scientific, and Technical Services. In this research, we have decided to eliminate legal (NAICS-5411) and accounting (NAICS-5412) services as professional services do not have a technological component. Therefore, we only consider scientific and technical services. That is the reason why in this study we refer to this sector as Scientific and Technical Services.

Before survey implementation, three innovation managers validated the questionnaire, so questions were clear and easy to understand. During November 2019, firms were randomly contacted by phone, with the aim of maintaining equal representation of analyzed industries. Firms were contacted via Computer-Aided Telephone Interviewing (CATI). This method is cost effective and can measure behaviors of interest (Couper & Hansen, 2002). Surveying yielded a sample of 116 firms. The response rate of 11.37% (116/1,020) is common in survey procedures in which social researchers have neither personal network nor relevant referral (Chidlow et al., 2015). Financial and accounting information for responding and non-responding firms is available through another BvD service, SABI database (https://sabi.bvdinfo.com). This information is important to ensure the objectivity of the values of interest, including number of employees, profits and productivity. The employment figures also serve to assess the importance of non-response bias in this study by comparing respondents and non-respondents. On average, respondents have 22.43 employees and non-respondents 20.89 employees. The t-test shows no statistically significant differences between respondents and non-respondents at the usual levels (p-value >0.1).[6]

3.2. Key variables

This study seeks to scrutinize firms' product strategy by unravelling the adoption of smart and connected products. Since Porter & Heppelmann's (2014) framework is nested, we first enquired about the adoption of initial stages of product analytic capabilities and subsequently progressed on to more advanced stages. The first stage is *Monitoring*. We consider that a firm reaches this stage if the following question is answered positively, *"Does your company use sensors to monitor the conditions, the environment, the activity carried out or the use made of any of its products?*". A total of 74 firms answered this question negatively and were classified as firms with *non-connected* products. The remaining 42 firms were asked about the adoption of the second stage, *Control*, using the following question "*Does your company use software incorporated into any of its products and cloud support to control its functions and user experience?*". Some 15 firms answered negatively and were classified as firms whose products have *monitoring* analytic capabilities. The remaining 27 firms were questioned about the adoption of the third stage, *Optimization*, by asking, "*Does your company have algorithms*

[6] We have undertaken similar tests for productivity and profits, and no significant differences for those variables are found.

designed to optimize the functions and use of any of its products?". As a result, 14 firms were classified as having products with *control* analytic capabilities due to their negative answers. Finally, in order to uncover which of the remaining thirteen firms offer *autonomous* solutions we asked two independent questions. (i) "*Do you consider that the combination of monitoring, control and optimization capabilities has allowed the company to develop additional product-related capabilities such as autonomous operation, improvement and customization?*" and (ii) "*Do you think that these capabilities have allowed the company to develop additional competences related to the service they offer such as self-coordination and self-diagnosis?*". A total of 11 firms answered both questions positively and are classified as offering *autonomous* solutions. The remaining 2 were classified as firms whose products have *optimization* analytic capabilities.

One important independent variable in our analysis is firm internationalization strategy. Following previous research, we include in the survey two different measures for the degree of firm internationalization, which depend on whether we look at foreign sales (*exports*) or at foreign production (*production abroad*). Export intensity is the ratio between total exports and total sales (Boehe, Qian, & Peng, 2016; Vaillant, Lafuente, & Bayon, 2019). On average, firms export 25.2% of their sales. Production abroad is the ratio between foreign production and total production (Jabbour, 2010). On average, in our sample 22.8% of the production is performed abroad.

Another dimension included in the survey is market strategy. There are two factors considered. First, we analyze offer *hybridization*. By construction, all firms in the sample operate in multiple industries. However, as a precautionary measure, firms were asked whether they were active in both manufacturing and service sectors. Some 48 firms answered that their operations have this hybrid component as they declare themselves to generate revenue streams from products, services or a joint product-service offer. Secondly, we enquired whether their market focus was towards other firms or final consumers. A total of 62 firms answered that they are focused on the *business-to-business* (B2B) domain.

The analysis also contains some continuous measures obtained from SABI that yield an indication on size, age, profitability and productivity. Firm size is the *number of employees*. *Firm age* is the difference between current year and the firm's year of foundation. Age has been included in previous studies as an important control variable and results seem to indicate that firm age has an influence on firm growth (Bustinza et al., 2018). The average firm in the sample has 22.43 employees and has been in operations for 23.62 years. Firm profitability is measured through the *EBITDA margin* indicating how much earnings the company generates before interest, taxes, depreciation, and amortization, as a percentage of total revenues. The average firm retains 10.4€ for each 100€ of revenue. Finally, *Labor productivity* is the ratio of total revenues over number of employees (Pessoa & Van Reenen, 2014). On average, each employee generates 170,940€ in revenues.

3.3 Methods

The study contains two sets of arguments that need to be tested. The first set of arguments focus on uncovering connected products' adoption enhancing factors. For that purpose, we use binary choice regression (Logit) in which we test the likelihood of having connected products. More precisely, for a given firm, the probability to adopt connected products is linearly related to a vector of observable variables (e.g. firm internationalization and hybridization), and non-observable factors that are absorbed in the error term. The firm's probability to adopt connected products cannot be directly observed but we know the actual outcome, which is defined as "1" when firm's products have at least the *monitoring* feature (42 firms) and "0" otherwise (74 firms). With this approach, we estimate the direct effects of firm internationalization (H1) and firm hybridization (H2) on the probability of adopting connected products, as well as, their mutually reinforcing effect defined by the interaction term (H3).

The second set of arguments seeks to uncover smart products' optimal configurations. To evaluate optimal configurations, we use a non-parametric technique, fsQCA. There are several reasons as to why this is an appropriate method. First, fsQCA uses Boolean algebra to implement principles of comparison (Ragin, 2008; Roig-Tierno, Huarng, & Ribeiro-Soriano, 2016). Conversely to multivariate methods as Structural Equations Modelling (SEM) where variables are analytically distinct and analyzed as separate, fsQCA study each case as a configuration of conditions where solutions represent specific combinations of causally relevant conditions linked to an outcome. In the current study we are thus selecting fsQCA due to its algebraic logic based on set-theoretic union, intersection and complementation, the relative multiplication, and conversion (Jonsson, 1984). That is because we are not analyzing the separate "net" effect of monitoring, control, optimization, and autonomy but the configuration of those conditions (overall effect) leading to superior performance. Second, according to Grofman and Schneider (2009), fsQCA techniques allow to better understanding causal complexity in terms of equifinality (different combinations of variables can be associated with the same outcome), conjunctural causation (neither single variables, nor additive combinations, but in conjunction to become causally relevant), and asymmetric causality (occurrence or non-occurrence of a casual condition require separate analyses). Third, fsQCA offers more detailed analyses than other techniques as it allows testing causation as a result of the interaction between conditions (Schneider & Wagemann, 2010). Fourth, fsQCA follows a deterministic logic instead of a probabilistic one, therefore having some particularities. As stated above, probabilistic methods such as multivariate techniques are focused on estimating the net effect of one variable on another considering the other variables constants (Ragin, 2008). Therefore, when two variables are strongly correlated (over-determination) their independent effects on a variable will be low. In Social Sciences, however, when phenomena overlap, they tend to reinforce each other. Overall, fsQCA is a paradigm shift from symmetric to asymmetric approach in terms of analyzing net effects instead of effect size (Woodside, 2013). It is useful for addressing theoretical hypothesis (Longest & Vaisey, 2008) where multiple variables appear in tandem or conjunction (in the current study, Smart-products analytic capabilities) at specific levels (presence-absence) to produce particular outcomes (in the current study, profit margin and labor productivity). In fsQCA, a case is understood as a configuration of explanatory conditions, being a configuration of a specific combination of factors behind the outcome of interest (Rihoux & Ragin, 2009). Explanatory conditions are not studied in isolation but in conjunction to produce an outcome. Therefore, it is a holistic approach to the cases, respecting their complexity and uniqueness throughout the entire analysis (Medina et al., 2017). An explanatory condition is necessary if it must be present for an outcome to occur and it is sufficient if it can produce a certain outcome by itself (Ragin, 2008).

fsQCA analysis offers different solutions when considering all the cases under study without excluding outliers. This is very useful for studies, like the present one, with low or medium population. In this sense, it offers different solutions: a) complex solutions where the counterfactuals or logical remainders are not taken in consideration, b) parsimonious solution when the counterfactuals are included and processes by the software, and c) intermediate solution where the researchers justify which counterfactuals are included. The intermediate solution is the recommended one as it offers the most parsimonious solution allowing maximum complexity (Ragin, 2008). There are two indicators associated to the obtained solutions: Solution Coverage that indicates how many of the cases with the result of interest are covered by the solution, and Solution Consistency that indicates how many of the cases covered by the settings have the result of interest (Medina et al., 2017). In order to operationalize our framework we will estimate the intermediate solution for a number of subsamples, so we can test optimal configurations for the full sample (H4), the sample of hybrid firms (H5) and the sample of fully internationalized firms (H6). Moreover, as a robustness exercise, we account for observed factors that lead some firms to self-select into adopting remote monitoring technologies by implementing a propensity score matching technique based on the estimates of the Logit analysis (see Deheija & Wahba, 2002). Therefore, we also run the intermediate solution for a matched sample that ensures comparability between firms with and without connected products.

We acknowledge that fsQCA has some limitations. For instance, it cannot analyze longitudinal data, nor provide an explanation about the influence of previous cases over later cases (Goldthorpe, 1997). There are some new methodological developments such-as TQCA (temporal QCA) that considers the temporal succession of factors to produce an outcome. But these are incompatible with the structure of the data used in this study. Additionally, as explained above, fsQCA is useful when researchers have information about presence/absence of a causal condition (Marasini, Quatto, & Ripamonti, 2016). Our casual conditions are crisp (i.e., dichotomous) and can be identified through a membership function, that returns the value 1 ‘‘true’’ if and only if the firm had actually installed a software for developing the different product analytic capabilities (Monitoring, Control, Optimization, and Autonomy). While this is our case, there are other approaches under the fuzzy theory that deal with certain characteristics of causal conditions that do not apply to our data. These other approaches help to operationalize information insufficiency (grey theory), inconsistencies in information (rough set theory), membership degree, non-membership degree, and hesitation degree (intuitionistic fuzzy sets), and functions to returns on a set of membership values for each casual condition (hesitant fuzzy sets).

4. Results

4.1. Descriptive evidence

Based on descriptive evidence shown in Tables 2 and 3, we present six stylized facts about the firm's adoption of connected and smart products that will enthuse our interpretation of results.

[Insert Tables 2 and 3]

First, the adoption of connected goods is a frequent activity. The development of their smart analytic capabilities, however, is much rarer. We observe in our sample that slightly more than a third of firms (36.2%) include features to their products that increase their connectedness. This means that the use of sensors or similar technologies is rather common in the business landscape. However, only one quarter of firms with connected products include additional features to develop full smartness capabilities from their products. Consequently, only 9.4% of firms offer autonomous solutions.

Second, the proportion of firms with connected and smart products depends on the firm's primary industry. Firms with scientific/technical services as first sector (NAICS-54) are much more likely to implement connected and smart products than firms with manufacturing (NAICS-32 and NAICS-33) as their first economic activity. In our sample, 45.2% of firms in NAICS-54 offer products with sensors. This figure is considerably lower (31%) for firms in manufacturing industries. This difference is even more pronounced when looking at the adoption of autonomous solutions. In relation to manufacturing, the proportion of firms offering autonomous solutions is three times higher in firms with NAICS-54 as their primary industry (16.7% vs 5.3%).

Third, firm size matters, but only for adopting autonomous solutions. On average, firms in the sample have 22.4 full time equivalent employees. To see the importance of firm size on the adoption of product analytic capabilities, we can divide the sample in three. Firms without sensors, firms with sensors but not achieving full product autonomy (monitoring, control and optimization), and firms that adopted product autonomy. Average firm size for the first two groups is practically identical (18 and 22 employees respectively); however, the latter group has a considerably larger average firm size (54). This indicates that size is not a barrier to adopt sensors, but it can be an important barrier for implementing fully smart and autonomous solutions.

Fourth, the degree of firm internationalization matters in adopting sensors. Firms that adopt sensors have on average more export sales than firms that do not adopt sensors (32.7% vs 21.0%). Similarly, firms that adopt sensors have higher degrees of production abroad than firms that do not adopt sensors (31.6% vs 17.7%). For firms that adopt sensors, firm internationalization does not seem to influence the degree of product smartness. For instance, firms that implement autonomous solutions have on average practically the same production abroad than firms adopting sensors in the absence of full product autonomy (30.7% vs 31.9%).

Fifth, in our sample, firm hybridization has a small but important effect in incrementing the proclivity to adopt connected and smart products. Firms that adopt sensors are more likely to have a hybrid nature than firms that do not adopt sensors (45.2% vs 39.2%). Finally, proclivity to adopt sensors is largest in the B2B domain. Regardless of the degree of product autonomy, sensor adoption is much more common in B2B firms (43.5%) than in B2C firms (28.5%). Despite being equally distributed (53% vs 47%) in the full sample, the proportion of B2B firms that adopt sensors is much larger than for B2C firms (64% vs 36%).

4.2. Analyzing the adoption of connected products

Table 4 presents the results of estimating binary choice model (Logit). The model has good fit with a pseudo-R^2 of 13-14%. Two ex-post exercises validate the fit of the model. First, the model correctly classifies 67-68% of the observations, with a balanced distribution between sensitivity (62-64%) and specificity (67-70%). Second, the C-statistic (or area under ROC) is above the commonly accepted threshold of 0.7 in all models.

[Insert Table 4]

Hypothesis 1 proposes that more internationalized firms have greater likelihood of implementing remote monitoring technology. We test this hypothesis using the two measures of firm internationalization available. Results only support the measure capturing foreign production. According to Model 1, when the other variables remain constant, increasing foreign production intensity by 1% leads to the increases the probability of adopting connected products of 0.004 percentage points. This result is significant at 1% (P-value < 0.01).

Hypothesis 2 proposes that hybrid firms have greater likelihood of implementing remote monitoring technology than non-hybrid firms. Our results support this hypothesis. According to Model 1, and considering that all other variables are held constant, the probability of adopting connected products is 0.101 percentage points larger for hybrid firms. This result is significant at 5% (P-value < 0.05).

Hypothesis 3 proposes that firm hybridization positively moderates the relationship between firm internationalization and connected product adoption. This effect is analyzed through the interaction term found in Models 2 and 3, which analyzes the interaction of hybridization with export intensity and foreign production intensity, respectively. As hypothesized, the parameter is positive and statistically significant in both models, suggesting that the effect of foreign sales and foreign production on the likelihood of adopting remote monitoring technology is significantly stronger in hybrid firms. Using Model 2 as an illustration, *et ceteris paribus*; increasing the interaction term by 1% increases the probability of adopting connected products by 0.003 percentage points. This result is significant at 1% (P-value < 0.01).

To help with the practical interpretation of the results, we plot the interaction terms between firm internationalization and firm hybridization assuming that the control variables are set at their sample means. Figure 3 shows that for hybrid firms both internationalization types (exports and foreign production) are conducive to a higher predicted probability of adopting connected products. In contrast, when considering non-hybrid firms this relationship flattens, or even turns negative in the case of exports.

[Insert Figure 3]

Our results demonstrate that there are various firm-level variables explaining the decision of adopting sensors. Since the objective of the upcoming analysis is to compare performance levels across firms with and without sensors, it is imperative to account for observed factors that lead some firms to self-select into adopting remote monitoring technologies; otherwise, results may be biased. A propensity score matching (PSM) technique was applied to construct comparable samples of firms with and without connected products. Propensity scores are based on the estimation of Model 1 in Table 4. A 1:1 nearest neighbor method without replacement was employed (see Deheija & Wahba, 2002). The PSM procedure resulted in a matched sub-sample of 70 observations (35 in each category). Table 5 shows the results obtained from the matching process, with emphasis on the mean differences in relevant variables before and after matching. As a result, a substantial bias reduction is observed in all cases. The Kolmogorov-Smirnov test also shows that the differences in propensity score distributions detected before matching disappear after the matching procedure.

[Insert Table 5]

4.3. Causal configurations that lead to superior financial and economic performance

The study uses fsQCA to analyze if membership in causal conditions (Monitoring, Control, Optimization, and Autonomy capabilities) is associated with higher outcome levels (profit margin and labor productivity). Therefore, using fsQCA enables the identification of those analytic capability-based combinations of causal conditions that are necessary and/or sufficient to explain economic and financial performance. In order to operationalize variables, they are calibrated from 0 to 1, establishing a crossover point of 0.5 that is the case boundary for being in or out of a condition. Causal conditions (smart product capability presence/absence) were naturally ranged from 1 (=”presence”) to 0 (=”absence”), while performance measures were ranged in a [1,0] interval by a fuzzy set calibration.

The first step in fsQCA is to analyze the coverage score. Table 6 shows that all product analytic capabilities (Monitoring, Control, Optimization, and Autonomy) are non-trivial conditions as their Coverage score yield a value clearly distant from 0. Taking a value near to zero would have meant that conditions occur in all cases, being theoretically and empirically trivial (Schneider & Rohlfing, 2016). Coverage can be interpreted as the coefficient of determination in regression analysis as it captures the amount of explained variation in dependent variables (Ragin, 2008, p. 63). As Thiem (2014) states, coverage value can be influenced by the choice of the crossover threshold and the membership function form –usually a piecewise logistic function is used to calibrate data as it is the default function available on the fsQCA software developed by Ragin, & Davey (2014) when the “direct method” is chosen. Sensitivity diagnostics is meant to explore if, depending of the relative location of the crossover threshold, changes in the membership function influence coverage in a positive or negative way (Thiem, 2014, p. 625). R software –QCAPro package (Thiem, 2018)– allows to select multiple functions: linear function (calibration by positive end-point concept), logistic (positive and corresponding negative end-point concept), quadratic/S-Shape (negative end-point concept), or inverted S-Shape (negative end-point concept). Because the study uses performance measures as its outcomes, a positive and corresponding negative end-point calibration approach was implemented. As a result, the membership function chosen was logistic.

[Insert Table 6]

The second step is to analyze the necessary conditions. In doing so, we adopt the *Consistence score* (Ragin & Davey, 2014). By convention, necessary conditions are those having a score ranging between 0.9 and 1. Table 6 provides consistency and coverage scores for all causal conditions for the full sample as well as all other samples of interest. Consistently with our theoretical predictions, only Monitoring has a consistency score above the 0.9 threshold for both outcome variables in the full sample. In order to assure that the results in the full sample are not contingent on firm selectivity into remote monitoring technologies, the analysis is also performed for the matched subsample. This yields similar results to the full sample. Therefore, for a general population of firms, Monitoring appears as a necessary condition to achieve the optimal outcome. This evidence falls in line with Hypothesis 4. Interestingly, when looking at the subsamples of hybrid and fully international SMEs, we also find support for Hypothesis 5 and Hypothesis 6, respectively. Control (but not optimization) is a necessary condition to achieve superior performance in hybrid firms, whereas Autonomy is a necessary condition to achieve superior performance in fully international SMEs.

The third step in fsQCA is to analyze the sufficient conditions/configurations to achieve optimal performance. In line with the hypothesized conditions, in Table 7 we test sufficient configurations for the full sample (TP1) and the subsamples of hybrid (TP2) and fully international (TP3) SMEs. Because of the nested nature of smart product capability levels (see Porter & Heppelmann, 2014) we adjust the causal configuration conditions accordingly. Autonomy represents the casual combination of all analytic capabilities: Monitoring (MNT)+Control (CTL)+Optimization (OPT)+Autonomy(AUT)[7]. We follow the same approach for Optimization=MNT+CTL+OPT, and Control=MNT+CTL. Moving to the fsQCA analysis, a threshold consistency score (OSCe) of 0.8 for the condition is linked to a value of 1 for outcome. The fuzzy truth table algorithm standard analysis reports three solutions: complex, parsimonious and intermediate. Following the established conventions, we use the intermediate solution to interpret the results (Ragin, 2008).

[Insert Table 7]

Results for the full sample show that there is only one sufficient condition for the outcome, Monitoring. The solution yields overall consistency values above 0.8 (OSCe = 0.834 for financial performance and OSCe = 0.827 for economic performance). Monitoring is the only

[7] In fsQCA standard terminology, UPPERCASE (lowercase) letters represent capability “PRESENCE” (“absence”).

causal condition that has coverage scores (raw and unique) meaningfully higher than 0 (Schneider et al., 2010), it is therefore the only solution reported in Table 7. The result is consistent with selectivity into remote monitoring technology bias, since the results on the matched subsample are qualitatively the same as the ones of the full sample. Overall, results confirm the prediction made in Hypothesis 4.

When analyzing the sample of Hybrid firms, the configuration that achieves superior financial performance is MNT+CTL; while the configuration that achieves superior economic performance is MNT+CTL+opt. This means that in regards to profit margin, hybrid firms are indifferent to develop analytic capabilities beyond Control, i.e. firm performance is undistinguishable across products achieving optimization or control analytic capabilities. However, hybrid firms obtain superior labor productivity if developing Control in the absence of Optimization analytic capability deployment (see raw coverage and unique coverage scores in Table 7). The result that Control is a sufficient condition for hybrid firms to achieve superior performance validates Hypothesis 5 and indicates that hybrid firms benefit from algorithm-based analytic capabilities.

When analyzing the sample of fully internationalized SMEs, the configuration that achieves greatest economic and financial performance is Autonomy. This is the only solution with unique coverage meaningfully higher than 0. The result that Autonomy is a sufficient condition for fully internationalized firms to achieve superior performance fully supports Hypothesis 6. It suggests that firms producing and selling abroad obtain financial and economic gains by developing autonomous analytic capabilities.

5. Discussion and conclusion

5.1. Discussion of key findings

The research presented in this paper provided an in-depth empirical investigation examining two separate research questions, essential for understanding the framework surrounding connected and smart products (Porter & Heppelmann, 2014, 2015). On the one hand, the study explored the firms' adoption of remote monitoring technology whilst identifying the selection factors that differentiate firms on the basis of their use of remote monitoring systems. On the other hand, the analysis reveals the optimal configurations of product analytic capabilities based on the standard framework of nested smart product classification developed by Porter &

Heppelmann (2014), which depends on the product's degree of connectivity and smartness. This classification progresses through Monitoring, Control, Optimization and Autonomous analytic capabilities.

By responding to recent calls for studies that quantitatively assess the implementation of autonomous solutions (Kohtamäki et al., 2019; Parida et al., 2019), the research presented in this paper depicts the dynamics of change in digital transition by providing unique evidence of the rate of adoption of connected and smart products in industrial SMEs. On the positive side, the research shows that the adoption of remote monitoring technology is relatively common amongst industrial SMEs, as 36.2% of firms claim to offer connected products. However, on the negative side, our evidence suggests that delivery of autonomous solutions applies only to one quarter of the firms that offer connected products and roughly one tenth of all firms. There is the expectation that these figures will increase over time, as more firms will adopt digital technologies. Our research sets a methodological approach for future investigations and business observatories to assess the rate of adoption of digital technologies across industrial firms.

Regarding the adoption of remote monitoring technologies, it is found that the current internationalization and hybridization strategic trends were significant factors driving firms to adopt real time monitoring systems through connected devises. When examining the performance implications of this digital capacity development, a clear association between the degree of product smartness and firm performance was found. In particular, the necessary and sufficient conditions that explain superior economic and financial performance were identified and formulated into a set of hypotheses. A novel non-parametric method to study the decisional outcome trajectories (fsQCA) was then used on a sample of 116 Spanish industrial SMEs to test the predictive validity of the stated hypotheses. The resulting findings show that autonomous solutions are not necessarily conducive to sustained improvements in performance in the case of domestic firms. This would tend to suggest that the implementation of autonomous solutions is more favorably applicable to a limited group of firms that have international exposure.

It is important to note that the modelled hypotheses are generally accepted, but that there are two tests that have not been fulfilled. First, the effect of internationalization on the adoption of sensors only comes out for foreign production, with the results for exports only becoming evident if the company is also hybridized (see Figure 3). Second, the product's degree of connectivity and smartness does not come out as a necessary and sufficient condition for hybrid firms to achieve superior performance if oriented towards Optimization (Hypothesis 5). Caution should be taken when interpreting this last result as it may be due to reduced sample size or other sample specificities resulting from the infrequent nature of this category. In our sample, most industrial SMEs adopting highly connected and smart production do not limit themselves to Optimization analytic capabilities but usually integrate Autonomous competencies as well.

5.2. Theoretical and managerial implications

The study draws at the interplay of three academic literature streams, namely smart products, digital servitization, and international business. We discuss in turn how the study contributes to each of these research streams and how its findings influence managerial practice in each domain.

The present research provides novel empirical evidence showing that product analytical capabilities enable firms to obtain superior performance. This important result has two ramifications. First, it confirms that data-intensive systems enable value-creation (Davenport et al., 2011). Second, analytic capabilities enable firms to overcome industry boundaries affecting their structure and provide new competitive competencies. This is consistent with Porter and Heppelmann (2014) who pointed out that smart products can reshape industry composition and competition. Based on these results, managers should focus their efforts on implementing smart systems that enables the use of products as data generation sources that can enlighten important managerial decisions.

The digital servitization literature already acknowledges the importance of combining hybrid offer with digital technologies (Coreynen et al., 2017; Vendrell-Herrero et al., 2017); however, it lacks explicit evaluation of the role of technologies on the enhancement of hybrid business models (Gebauer et al., 2020; Kohtamäki et al., 2020). The present study provides indications that remote monitoring technologies are more popular amongst hybrid firms. It also finds that monitoring capabilities are necessary and sufficient conditions to achieve superior performance in hybrid firms. These findings contribute to the digital servitization debate, as they explicitly pinpoint the strategic importance of remote monitoring technologies for servitized firms. From a practitioner perspective, our findings suggest that firms implementing servitization must adopt remote monitoring technologies as a strategic tool encouraging competitive advantage.

The international business literature is interested in studying how firms with a global presence can benefit from smart technologies. The literature is rich with conceptual frameworks, but lacks evidence (see Alcácer et al., 2016; Chen & Kamal, 2016). The few exceptions look at production location choices (see Dachs et al., 2019) and market characteristics (Parida et al., 2015), and not at performance implications. In this regard, the study indicates that firm internationalization is associated with greater adoption of remote monitoring technology, and that fully internationalized SMEs (with both foreign sales and production) are the ones that most benefit from autonomous solutions. Our results suggest that managers of exporting SMEs, and especially SMEs participating in global value chains, should adopt autonomous solutions as they improve global network coordination (Rezk et al., 2016).

5.3. Methodological insights and data limitations

To measure the performance contribution of smart products in this study, both financial output and labor productivity were used as indicators. Previous studies have found that productivity and operating margins are not necessarily correlated (Anderson, Fornell, & Rust, 1997; Foster, Haltinwanger, & Syverson, 2008). It is therefore important to analyze the relationships between both these performance indicators. The results of our study, however, are consistent at different performance measures. This in itself is interesting because it means that the firm's analytic capabilities can not only engender greater productivity (which can be interpreted as a process of technology-labor enhancement) but also can increase the firm's economic margins (via greater value-added and competitiveness). In the context of smart products, it seems that both performance variables go hand in hand.

An important methodological contribution of this study comes from the empirical design adopted. Previous studies analyzing the adoption and consequence of economic events have used statistical regression models in two stages, i.e. studies jointly evaluating self-selection into exporting and then learning by exporting (Chang & Chung, 2017). These models require large databases and are conditioned on the fact that the event under study does not involve additional decisions. This is not so in our case. First, we work with a small database, and secondly, the adoption of connected products involves decisions as to the level of analytic capabilities (Smartness) of these products. It is impossible to know the true economic-financial impact of connected product adoption without also considering this related decision (as well as its business context) - see Figure 2. As a consequence of these two intricacies, it was decided to introduce an algorithmic analysis (fsQCA) for the second stage of the study's model. The study is therefore amongst the first to analyze the two stages (adoption and consequence) with a combination of parametric and non-parametric analysis, showing the potential synergies between these types of empirical methods.

Despite the uniqueness and richness of the data used in this study and of the appropriateness and rigor of the different methodologies used in its analysis, a number of limitations remain. First, despite the fact that the hypotheses developed to capture the factors driving the association between the degree of product smartness and firm performance were largely validated through the use of meticulously applied novel methods, more elaborate quantitative empirical research may be required in order to further investigate these links.

Second, we assume a standard framework for smart products based on prior conventions established in the related literature that universally fit across the products with connected and smart characteristics of all industries. However, our analysis does not account for cross-industry heterogeneity beyond that distinguishing manufacturing and technical/scientific service firms. Future studies on the optimal configuration of smart products, especially in the context of internationalization and hybridization, should include variables connected to the industrial specificity of these constructs. Additional research should expand to other potential business strategy trends beyond internationalization and hybridization that are likely to influence the adoption and optimal configuration of smart products.

Third, we conceptualize hybridization as a moderating variable and thereby it has been treated as a dichotomy. It means that future research considering hybridization as independent (or even dependent) variable should focus on the intensity of hybridization. This approach can also differentiate between hybrid firms that divide sales in multiple industries equally to hybrid firms that largely concentrate their sales in one specific sector. A further limitation relates to the cross-sectional nature of the data used in the study, which does not allow for longitudinal heterogeneity analyses. As a result, future work based on longitudinal data seems decisive to better understand the temporal evolution of smart product capability development. Finally, the conclusions generated in this study are the result of the analysis of Spanish industrial SMEs. Although this setting is justified for the specific needs of the current study, and it can reasonably be assumed that its findings and recommendations can be extended to organizations with more heterogeneous profiles, there remains a need for greater replication studies in many other contexts in order to confirm that this is so.

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Table 1. Survey technical specification

POPULATION	
Universe	Manufacturing and scientific/technical service firms (NAICS 32, 33, 54)
Source	ORBIS (Bureau van Dijk)
Geographical area	Established in Spain
Population	1,020 SMEs
Methodology	Structured questionnaire
INDUSTRIAL COMPOSITION OF THE POPULATION	
NAICS-32	18.2%
NAICS-33	39.2%
NAICS-54	42.7%
SAMPLING PROCEDURE	
Type of interview	CATI (Computer Aided Telephone Interviewing)
Sampling procedure	Simple Random Sample
Survey date	November 2019
Confidence interval	95.5% (p=q=0.50), *k=2*
Sample size	116 SMEs
Response rate	11.37%
Sampling error	+/- 5.86%
INDUSTRIAL COMPOSITION OF SAMPLE	
NAICS-32	27.6%
NAICS-33	36.2%
NAICS-54	36.2%

Table 2. Average profile of the sampled firms by industry

	Source	Full sample	NAICS-32	NAICS-33	NAICS-54
			Printing, chemical and pharmaceutical manufacturing	Metal, machinery and hardware manufacturing	Scientific, and Technical Services
Observations		116	32	42	42
# Employees	Sabi	22.43	13.6	21.7	29.9
		(36.02)	(11.95)	(32.19)	(48.73)
Firm age	Survey	23.62	24.53	19.76	26.78
		(21.62)	(22.77)	(15.43)	(25.58)
Lab. Productivity (thousand €)	Sabi	170.94	185.18	157.97	173.07
		(144.04)	(150.32)	(93.11)	(179.19)
% EBITDA margin	Sabi	10.14%	11.54%	7.27%	11.95%
		(11.13)	(8.06)	(14.75)	(8.23)
% Export sales	Survey	25.25%	22.65%	24.83%	27.64%
		(32.14)	(28.90)	(32.05)	(35.04)
% Production abroad	Survey	22.78%	21.71%	24.88%	21.5%
		(30.70)	(28.81)	(32.01)	(31.35)
Hybrid firm	Survey	0.414	0.281	0.571	0.357
		(0.495)	(0.456)	(0.501)	(0.485)
B2B	Survey	0.534	0.562	0.571	0.476
		(0.501)	(0.504)	(0.501)	(0.505)
Monitoring	Survey	0.362	0.344	0.286	0.452
		(0.482)	(0.482)	(0.457)	(0.503)
Control	Survey	0.233	0.125	0.190	0.357
		(0.424)	(0.336)	(0.397)	(0.485)
Optimization	Survey	0.112	0.062	0.095	0.167
		(0.317)	(0.245)	(0.297)	(0.377)
Autonomy	Survey	0.094	0.062	0.047	0.167
		(0.294)	(0.245)	(0.215)	(0.377)

(Standard Deviation in parenthesis).

Table 3. Average profile of the sampled firms by product connectedness and smart capabilities

	No connected	Monitoring	Control	Optimization	Autonomy
Observations	74	15	14	2	11
# Employees	17.84	26.16	18.22	19.85	54.09
	(25.17)	(27.38)	(20.64)	(2.61)	(85.91)
Firm age	19.74	37.93	30.64	16.00	22.63
	(11.86)	(43.52)	(28.13)	(4.24)	(12.89)
Lab. Productivity	163.56	213.15	147.18	164.30	194.48
(thousand €)	(144.77)	(210.21)	(77.46)	(11.82)	(107.04)
% EBITDA margin	9.67%	10.95%	9.84%	7.48%	12.42%
	(12.33)	(7.22)	(7.17)	(0.30)	(12.89)
% Export sales	20.98%	33.33%	29.11%	20.00%	38.96%
	(31.62)	(33.10)	(32.63)	(28.28)	(33.43)
% Production	17.75%	37.33%	27.96%	20.00%	30.68%
abroad	(29.51)	(32.40)	(31.82)	(28.28)	(31.62)
Hybrid firm	0.392	0.533	0.428	0.000	0.454
	(0.491)	(0.516)	(0.513)	(0.000)	(0.522)
B2B	0.473	0.733	0.500	1.000	0.636
	(0.503)	(0.457)	(0.518)	(0.000)	(0.504)

Product capabilities are determined by top-level of product connectedness-smart achieved by the firm. (Standard Deviation in parenthesis).

Table 4. Logit: Propensity to product connectivity

	Model 1	Model 2	Model 3
# Employees	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
% Export sales	-0.000	-0.002***	-0.000
	(0.001)	(0.000)	(0.001)
% Production abroad	0.004***	0.004***	0.003***
	(0.001)	(0.001)	(0.001)
Firm age	0.006***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)
Hybrid	0.101**	0.013	0.039
	(0.045)	(0.043)	(0.062)
B2B	0.148	0.134	0.141
	(0.106)	(0.096)	(0.104)
Hybrid*Export sales		0.003***	
		(0.001)	
Hybrid*Production abroad			0.003***
			(0.001)
Observations	116	116	116
Industry FE	Yes	Yes	Yes
Pseudo R^2	0.1338	0.1444	0.1397
Area under ROC	0.713	0.721	0.717
Correctly classified (cut off = 36.2%)			
• Sensitivity	61.9%	64.3%	64.3%
• Specificity	67.6%	70.3%	68.9%
• Overall	65.5%	68.10%	67.2%

Parameters reported are marginal effects
Robust Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5. Propensity score matching (PSM) results

Variables	**Difference in means (Before)**	**T-test P-value (Before)**	**Difference in means (After)**	**T-test P-value (After)**	**Reduction bias (%)**
# Employees	12.68	0.06	3.16	0.49	75.08%
% Export sales	11.78	0.05	3.67	064	68.85%
% Production abroad	13.88	0.01	1.10	0.88	92.07%
Firm age	10.71	0.00	-0.14	0.96	101.31%
Hybrid	0.060	0.52	0.065	0.48	-8.33%
B2B	0.169	0.07	-0.028	0.81	116.57%
NAICS-32	0.021	0.80	0.028	0.79	-33.33%
NAICS-33	-0.12	0.20	0	1.00	100.00%
NAICS-54	0.14	0.12	-0.028	0.80	120.00%

* 1:1 nearest neighbour without replacement and calliper equals 0.1.

** We conducted the Kolmogorov-Smirnov test (KS). Whilst the difference between PSM distribution was significantly different before matching (combined KS = 0.3417, p-value = 0.004), it turns considerable non-significant after matching (Combined KS = 0.1143, p-value = 0.976).

Table 6. Analysis of necessary conditions

	Financial performance		*Economic performance*	
Condition	*Consistency*	*Coverage*	*Consistency*	*Coverage*
Full sample (116 firms)				
Monitoring capability	0.932	0.707	0.924	0.712
Control capability	0.834	0.678	0.856	0.696
Optimization capability	0.708	0.632	0.711	0.639
Autonomy capability	0.523	0.641	0.528	0.654
Matched sample (70 firms)				
Monitoring capability	0.916	0.719	0.912	0.704
Control capability	0.806	0.688	0788	0.682
Optimization capability	0.698	0.642	0.686	0.632
Autonomy capability	0.558	0.638	0.532	0.622
Hybrid firms (48 firms)				
Monitoring capability (MNT+CTL)	0.910	0.693	0.902	0.672
Optimization capability	0.786	0.633	0.802	0.640
Autonomy capability	0.604	0.602	0.642	0.604
Fully internationalized SMEs (54 firms)				
Autonomy capability (MNT+CTL+OPT+AUT)	0.918	0.728	0.896	0.688

Table 7. Smart product's capabilities configuration and performance

	Outcome variables							
	Financial performance (EBITDA, margin)				**Economic performance (Labor productivity)**			
Capabilities of smart products	Smart product capabilities continuum				Smart product capabilities continuum			
	Monitoring	Control	Optimization	Autonomy	Monitoring	Control	Optimization	Autonomy
Full sample (116 firms)	●	—	—	—	●	—	—	—
	R = 0.743 / UC = 0.347 / C = 0.693 OSCe = 0.834 / OSCs = 0.712				R = 0.720 / UC = 0.354 / C = 0.692 OSCe = 0.827 / OSCs = 0.698			
	Intermediate solution	Raw coverage	Unique coverage	Consistency	Intermediate solution	Raw coverage	Unique coverage	Consistency
	Mnt *Ctl*	**0.743** *0.343*	**0.347** *0.011*	**0.693** *0.684*	**Mnt** *Ctl*	**0.720** *0.339*	**0.354** *0.008*	**0.692** *0.689*
Matched (70 firms)	●	—	—	—	●	—	—	—
	R = 7.458 / UC = 0.367 / C = 0.732 OSCe = 0.876 / OSCs = 0.739				R = 0.763 / UC = 0.367 / C = 0.735 OSCe = 0.868 / OSCs = 0.741			
Hybrid (48 firms)	Control (Monitoring+Control)		Optimization	Autonomy	Control (Monitoring+Control)		Optimization	Autonomy
	●		○	—	●		—	—
	R = 0.762 / UC = 0.259 / C = 0.727 OSCe = 0.868 / OSCs = 0.741				R = 0.759 / UC = 0.262 / C = 0.726 OSCe = 0.885 / OSCs = 0.731			
Fully internationalized (54 firms)	Autonomy (Monitoring+Control+Optimization+Autonomy)				Autonomy (Monitoring+Control+Optimization+Autonomy)			
	●				●			
	R = 0.735 / UC = 0.217 / C = 0.721 OSCe = 0.856 / OSCs = 0.732				R = 0.733 / UC = 0.234 / C = 0.728 OSCe = 0.857 / OSCs = 0.735			

Black circles "●" indicate that companies implement these capabilities; unfilled circles "○" indicate that they do not implement these capabilities, and a hyphen "–" indicates indifference. "C" means Consistency; "R" Raw coverage; "UC" Unique Coverage; "OSCy": Overall Solution Consistency; "OSCe": Overall Solution Coverage

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Figure 1. Smart systems and Product analytic capabilities generation

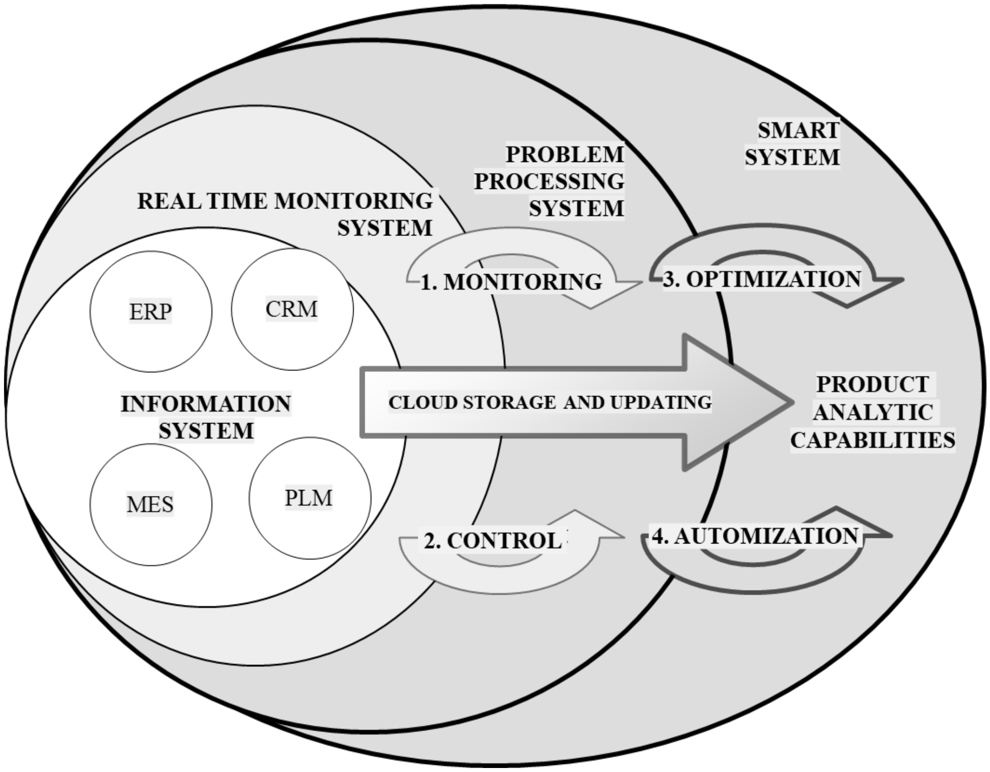

Figure 2. Theoretical framework

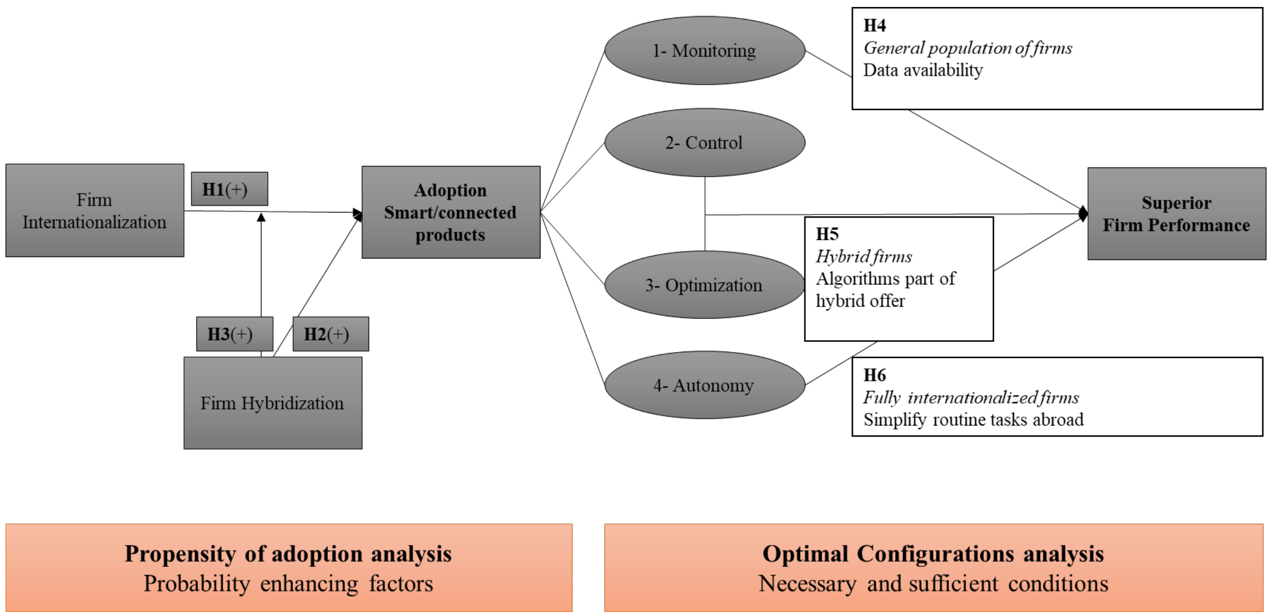

Figure 3. The moderation role of firm hybridization