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Is digital transformation equally attractive to all manufacturers? Contextualizing the operational and customer benefits of Smart Manufacturing

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Abstract

Purpose –The implementation of Smart Manufacturing (SM) is deemed a key enabler in the enhancement of manufacturing competitiveness and performance. Nevertheless, its repercussion on consumer perceptions and the contextualization of its performance-enhancement effects remains undetermined and have yet to be clarified. This study analyzes the effect of Smart Manufacturing on operational and customer performance. Moreover, it explores how these relationships change depending on a firm's geography of production (i.e., national/local vs. transnational operations) and the relational arrangement adopted (i.e., service-oriented vs. transaction-oriented manufacturers).

Design/methodology/approach – This research surveys 351 Spanish manufacturing firms operating in an SM environment. The theoretical framework comprises a Multiple-Indicators Multiple-Causes model and is tested using a Generalized Structural Equations Model.

Findings –The results obtained substantiate the positive effect of SM implementation on both of the performance measures analyzed (i.e., operational and customer-focused). Moreover, the study reveals that while geography of production moderates the effect on a firm's operational performance, relational arrangement also does so in terms of customer performance.

Originality/value–This research clearly differentiates the benefits of SM depending on business context. In this regard, transnational production firms tend to gain in operational performance while service-oriented manufacturers gain in customer performance.

Keywords – Digital transformation, Smart Manufacturing, supply chain structure, relational arrangement, servitization, business performance.

Paper type – Research paper.

1. Introduction

Digital transformation signifies a profound and hastened transition in manufacturing industries in order to fully leverage the opportunities brought about by digital technologies (Gölcük, 2020). Implementing digital technologies in the production system has become a crucial catalyst in order to transform supply chains into smarter systems, hence the concept of Smart Manufacturing (Leng *et al*., 2021). Smart Manufacturing (SM hereafter) refers to a digitally integrated manufacturing system that enables real-time responses to the changing conditions of production processes, customer needs and demands, and the business ecosystems in which manufacturers operate (Kusiak, 2018). Together with big data and predictive analytics, which enable manufacturing firms to make wiser decisions, SM is rapidly and increasingly becoming a key aspect in terms of corporate operational strategy (Wamba *et al*., 2020a) and, therefore, of performance (Raguseo and Vitari, 2018; Wamba *et al*., 2020b). Indeed, SM is closely linked to core strategic competency development such as increased product development capabilities (Wamba *et al*., 2017), continuous production optimization (Gunasekaran *et al*., 2017), enhanced supply chain collaboration and co-creation capacity (Sodero *et al*., 2019), business model innovation (Gambardella and McGahan, 2010) and improved delivery solution faculties (Vendrell-Herrero *et al*., 2021a). In short, SM is functionalized in four main modules: Manufacturing-based, Data-driver, Real-time monitoring and Problem-processing, all of which employ different technologies (e.g., sensors, cloud storage, the Internet of Things, big data, artificial intelligence and so on) and are linked to differentiating strategic benefits such as enhanced competitiveness, customer alignment, innovation and core business consolidation, respectively (Kozjek *et al*., 2020).

While SM-induced competencies have been associated with the increased operational performance of companies implanting such smart processes (Wamba *et al*., 2020b), their effects on consumer perceptions remain underexplored, and thus warrant due attention. Since many SM-derived capabilities directly results in the development and delivery of greater consumer value (Akter *et al*., 2020), deductive reasoning thus leads us to believe that the implementation of such technological and operational processes will have a positive impact on customer performance.

Nonetheless, the impact of SM on operational and customer performance measures will likely require contextualization. Initially, from an input/output perspective, geography of production (i.e., national/local and transnational production) is a key determinant in terms of effective SM implementation (Morelli *et al*., 2020). The entry costs and learning curve involved in SM implementation are such that transnational production firms which can spread investment over broader international production structures wield an advantage. Also, the organizational and operational complexity of transnational production structures are more likely to obtain higher added value and output, and offset the resource allocation required for appropriate SM implementation (Oliveira *et al*., 2021). Similarly, from the perspective of absorptive capacity, transnational production firms are generally characterized as having greater transformation and assimilation capacities, making them more apt to better adopt and integrate SM processes (Todorova and Durisin, 2007; Müller *et al*., 2021). As such, geography of production may well moderate the relationship between SM adoption and performance, namely operational performance.

However, as regards customer performance, the impact of SM is far more likely to be influenced by the firm's service orientation or lack thereof (Rymaszewska *et al*., 2017). In this respect, SM-induced servitization tends to stimulate relationship-based, rather than transaction-based, interactions between manufacturers and their customers (Oliva and Kallenberg, 2003; Vendrell-Herrero *et al*., 2023). SM technologies are crucial to the solution delivery model underlying service-oriented firms as they enable customized value-creation that is specifically incentive-designed to influence customer behavior and satisfaction (Neely, 2008; Tao and Qi, 2017; Opazo-Basáez *et al*., 2022). Therefore, the service orientation of producers may well moderate the relationship between SM adoption and performance, namely customer performance.

This study aims to determine whether the implementation of Smart Manufacturing modules relates positively to operational and customer performance, and whether geography of production and the relational arrangement (i.e., service-oriented vs. transaction-oriented) adopted by manufacturing companies moderate this relationship. In order to achieve this research objective, the study employs a Multiple-Indicators Multiple-Causes model (Vendrell-Herrero *et al*., 2021b), estimated by Generalized Structural Equation Modeling, and using a self-devised primary database comprising 351 Spanish manufacturing firms.

Several important contributions to the current literature on Smart Manufacturing performance are made by this study. First, it responds to the calls made by Gölgeci *et al*. (2021) and Das and Dey (2021) for further research and literature on the application of SM and its differential impacts when implemented within transnational production structures or servitized contexts. The different SM technological modules are not only detailed in relation to their technologies and potential operational and strategic benefits, but are also contextualized on the specific basis of their geography of production and service-orientation. This enables the study to ascertain that, on the whole, it is more challenging for firms dependent on local production to reap the operational performance benefits of implementing Smart Manufacturing modules. Nonetheless, despite the fact that operational performance benefits are constrained by geographical location of production, servitization is a means to access customer performance benefits and offset the constraints on SM implementation in local production firms.

2. Background literature and hypotheses development

2.1. Smart Manufacturing: a theoretical perspective

SM can be defined as the intensified and pervasive application of data-based technologies that are networked across the entire manufacturing and supply chain (Davis *et al*., 2012). It constitutes a new, digitally-driven manufacturing system that is fully connected via wireless networks monitored by sensors and controlled by advanced computational intelligence (Wang *et al*., 2018a). By leveraging these advanced technologies in manufacturing, real-time data from varying sources across different supply chain systems (ranging from raw materials, machine operations, facility logistics, and even human operators) is collected and processed (Lu *et al*., 2014). As a result, manufacturing firms on different scales can benefit from data analytics (i.e., data collection, processing and visualization) in order to broaden their understanding of customers, competitors, products, equipment, processes, services, employees, suppliers and so on, and can thus make more rational, responsive and informed decisions in order to enhance their competitiveness (Tao *et al*., 2018).

To date, the study of SM has been addressed from differing operations-related research domains including production planning, plant scheduling, product customization, flexible manufacturing, fault identification and recovery, to name a few (Phuyal *et al*., 2020). Similarly, the study of SM has been approached from multiple theoretical frameworks (e.g., Resource-based view theory, Socio-technical systems theory, Institutional theory, Chaos theory, Stakeholder theory, etc.). In this sense, it is relevant to highlight that the different theoretical lenses offer clear evidence that SM implementation is a determining factor when it comes to providing firms with a series of operational performance benefits, among which the following are notable; profitability, production control, production efficiency, capacity, production speed, quality, management support and cost efficiency (Duman and Akdemir, 2021).

In order to provide a clear understanding of the SM concept from a theoretical standpoint, Table 1 combines the different theoretical lenses under which the SM concept has been assessed and scrutinized from a performance perspective. Moreover, and for comparative purposes, in each case a seminal contribution and concise description of each theoretical viewpoint's generic rationale is included. In addition, a context-specific study along with its context-specific focus is presented. As a whole, this categorization intends to provide a reference guide to the different theoretical grounds leading to the current literature on SM and performance, while also serving as a benchmark that can be used to elucidate the multiple theoretical standpoints where SM is shown to possess the potential to provide operational performance benefits.

--- Insert Table 1 hereabouts ---

2.2. Smart Manufacturing: a descriptive perspective

SM is a networked paradigm combining several technologies such as the Internet of Things (IoT), big data and predictive analytics (BDPA), industrial internet and artificial intelligence (Ren *et al*., 2019). The IoT constitutes the infrastructure that allows big data to access and gather data via real-time monitoring, while the BDPA concept encompasses problem-processing systems oriented toward handling the data in terms of its capture, storage, transfer and sharing for predictive application (Gunasekaran *et al*., 2017). Artificial intelligence –another problem-processing system–lies behind the new, smart products framework, and is characterized by integrating monitoring, control, optimization and autonomous decision-making (Porter and Heppelmann, 2015).

SM embraces multiple technologies implemented in firms and networks oriented toward connecting, monitoring and controlling products, services, machines and people (Wang *et al*., 2018a). As such, SM implementation is operationalized by means of four technological modules that co-operate, beginning with the Product-oriented Manufacturing module (MM), which is more traditional and incorporates software such as Enterprise Resource Planning (ERP), Manufacturing Enterprise Systems (MES), Customer Relationship Management (CRM) or Product Lifecycle Management (PLM) (Bustinza *et al*., 2021). A Data-driver (DD) module is then used to gather all the information from the system, not only on the human operators and production data generated from the aforementioned module, but on the entire industrial network. As for the third SM module, Real-time monitoring (RTM) is used to control and monitor the entire industrial network (Tao *et al*., 2017). The cloud-based DD module gathers big data from the MM, RTM and fourth module, Problem-processing (PP). The PP module identifies and predicts possible problems while suggesting plausible solutions that can be found by humans or artificial intelligence. In doing so, this module estimates effectiveness, evaluates impacts on operations, aids proactive maintenance and reports on actionable recommendations to the MM module (Tao *et al*., 2018). The relationship between the SM modules, technologies and benefits is shown in Table 2.

--- Insert Table 2 hereabouts ---

2.3. Smart Manufacturing and operational performance

SM's potential benefits relate to reducing costs, improving operational equipment and availability, increasing operational speed and improving product quality (Lafuente *et* *al*., 2019). The literature puts forward a comprehensive set of indicators to evaluate the benefits derived from SM implementation – cost, optimized productivity, quality, integration, flexibility and real-time diagnosis – which are basically backed up by traditional performance measures – quality, cost, delivery, flexibility, operational and strategic indicators (Kamble *et al*., 2020). With regard to the aforementioned benefits, the effects of data analysis on cost reduction, optimized productivity and quality stem from the Second Industrial Revolution. This was when raw data was used in early statistical models in order to enhance production planning, decrease failure rates or improve raw material consumption (Tao *et al*., 2018). Integration and flexibility were achieved by applying interactive information and manufacturing technologies to production, such as ERP or CRM. Real-time diagnosis was enabled through the use of the IoT in manufacturing. More recently, further developments such as BDPA and AI have made it possible for SM to have a positive influence at operational and strategic, organizational levels.

From an operational point of view, SM can potentially benefit many different aspects of production, such as flexibility, efficiency, quality, safety, reliability, availability and continuous optimization, as well as resource efficiency, product development and supply chain collaboration (Geißler *et al*., 2019). Production flexibility is defined as the set of part categories that can be generated by the manufacturing system, which can lead to substantial setups without adding major capital equipment (Sethi and Sethi, 1990). It allows firms to compete in markets where continuous new product development is a competitive weapon. Production efficiency relates to the capacity to produce a given product using fewer resources, thus contributing to a reduction in the number of inputs required for producing a standard output (Thatcher and Oliver, 2001). Production quality is understood as a system's production capacity, which follows pre-set requirements and specifications, and complies to acceptable production safety levels in terms of the functional safety of devices and production machinery (Sethi and Sethi, 1990). Production reliability is basically assessed according to the number of faulty items in relation to the total number of items produced during a given period of time. Product availability is the ratio between actual production and planned production, that is, it measures the system's capacity to comply with delivery or performance demands (Meng *et al*., 2018). Finally, continuous production optimization is achieved via SM by the enhanced predictive and monitoring approaches for the early detection of production faults (Sjödin *et al*., 2018).

Other potential operational benefits derived from SM implementation are resource efficiency, understood as the ratio between added product value and value of resources used in production (Di Maio *et al*., 2017; Vaillant *et al*., 2021); increased product development, understood as the capability to transform the original products that manufacturers have in their sales portfolio into new products due to knowledge captured (Kodama, 2008); and enhanced supply chain collaboration –the process of decision-making among interdependent parties involving mutual understanding and shared resources (Schrage, 1990; Stank *et al*., 2001). As for the effect on operational performance, SM implementation is associated with appropriate improvements in terms of manufacturing outputs and productivity (Wellener *et al*., 2019). Basically, when SM is suitably deployed, operational risks associated with loss due to unsuccessful in-house processes may be reduced. Hence, by combining data processing and process expertise, SM facilitates manufacturing decisions which, in turn, are deemed to improve operational performance (Lee *et al*., 2013). Therefore, while taking all these arguments into consideration, we hypothesize that:

Hypothesis 1: Smart Manufacturing implementation relates positively to operational performance.

2.4. The moderating role of geography of production

Geography of production is an important contextual variable in determining SM and operational performance (Ancarani *et al*., 2019). The academic literature related to national/local and transnational production chains actually diverges by and large (Harland, 2021). There are several differences between these types of corporate production structure. In terms of operational processes, they differ with regard to the varying manufacturing practices employed (Keijser *et al*., 2021). These practices relate to the specific capabilities of manufacturers that enable firms to compete in a larger number of markets (Vendrell-Herrero *et al*., 2020; Opazo-Basáez *et al*., 2021). Such competencies have become established processes and world-class manufacturing standards in order to improve operations management (Oliveira *et al*., 2021). According to these literature streams, national and transnational firms differ in how they manage their operational processes (Keijser *et al*., 2021). For example, some differences found in the literature between national and transnational production firms in terms of manufacturing practices relate to JIT (Gereffi, 2020), TQM (Saranga *et al*., 2019) or lean manufacturing (Cheng *et al*., 2021).

In the case of national/local production firms, stricter access to business markets, less complex operational setups and lower optimal production volumes mean that SM implementation may not have enough potential value to offset the important entry cost and learning curves involved (Morelli *et al*., 2020). National/local producers often require longer timescales to reap the operational performance benefits of surmounting the complexity of the SM implementation process (Raguseo and Vitari, 2018). In order to achieve optimal operational performance benefits from implementing SM modules, not only do firms need to be able to effectively implement and operate the technologies and advanced tools involved, but must also be able to interpret the intelligence generated in an appropriate fashion. The organizational resources and competency developments required for the true assimilation and/or transformation of in-house processes in order to adapt to effective SM module implementation often lie beyond the boundaries of the immediate and absorptive capacities and capabilities of nationally/locally-oriented incumbent manufacturers (Todorova and Durisin, 2007; Müller *et al*., 2021). The expected operational performance benefits from SM implementation may therefore be somewhat less attainable in the case of national/local production firms.

Moreover, previous studies suggest that transnational production firms are more likely to be confronted with coordination challenges (Opazo-Basáez *et al*., 2021) that hamper appropriate strategic implementation and performance (Paolucci *et al*., 2021). Introducing SM is a way of meeting such challenges, which, due to their scale, implies greater production efficiency and superior performance gains.

This would suggest that the effect of SM modules on operational performance is more pronounced in transnational than in national/local production firms. Therefore, we hypothesize that:

> **Hypothesis 1a**: Geography of production moderates the relationship between Smart Manufacturing and operational performance. Manufacturers with transnational production structures will therefore obtain higher operational performance from Smart Manufacturing.

2.5. Smart Manufacturing and customer performance

Regarding SM's potential strategic benefits, the literature describes positive effects related to an increased focus on core business, and intensive productivity growth (Fay and Kazantsev, 2018), business models innovation, competitiveness, product innovation and alignment between production and changing customer demands (Geißler *et al*., 2019; Belhadi *et al*., 2021). Technological advances enable firms to leverage a firm's skills, which can help it enter new markets whilst remaining focused on its core business (Depecik *et al*., 2014). By means of sensors, monitoring and computational control, SM improves productivity (Wang *et al*., 2018a), making the productivity growth curve concave. Business model innovation sustains competitive strategy by determining market segments more accurately, thus enabling firms to reduce the risk involved in uncertain demand (Girotra and Netessine, 2014). By relying on SM technologies to develop business model innovation, firms can create the commonalities needed to serve specific market segments more efficiently and, in turn, their customers (Vendrell-Herrero *et al*., 2021c; Shleha *et al*., 2022). Technologies operating under SM systems are able to extract value from big data, which is key to improving competitiveness (Altomonte *et al*., 2011; Qi and Tao, 2018). Furthermore, SM provides insight into market preferences and customer demand more accurately: the pillars of an appropriate design phase in product innovation. Finally, SM is backed up by monitoring, communication and control capabilities that create the alignment needed between firms and customers in order to offer a more immediate response to the dynamics of changing market demands (Wang *et al*., 2018b; Vendrell-Herrero *et al*., 2023). It can therefore be inferred that these increased interactions generate higher value-creation opportunities. Taking these arguments into consideration, we hypothesize that:

Hypothesis 2: Smart Manufacturing implementation relates positively to customer performance.

2.6. The moderating role of relational arrangements

Servitization constitutes a paradigm shift in manufacturing whereby manufacturers transform in order to develop service-oriented business models that expand by using a broad range of enabling digital technologies (Bustinza *et al*., 2020). In short, in this paradigm, products are no longer simply released onto the market; rather, business customer needs are provided with complex and highly customized solutions (Lafuente *et al*., 2019). The main differences between traditional (i.e., transaction-oriented) manufacturing firms and servitized (i.e., service-oriented) manufacturers stem from the fact that servitized producers focus their systems on improving interactions between production processes and service operations (Vendrell-Herrero, *et al*., 2021b; Vendrell-Herrero *et al*., 2023). For servitized manufacturers, organizational capabilities are underpinned by the customer information that is gathered and processed, and a shift in the notion of asset management, where services are specifically designed to meet evolving customer needs, and thus influence customer behavior (Neely, 2008; Bustinza *et al.,* 2019). Furthermore, training in product use, assistance and interaction are made possible by services developed through Smart Manufacturing technologies (Tao and Qi, 2017; Ghouri *et al*., 2021), which in turn drastically increases the producer's interactions and relationships with customers, all of which ensures customer satisfaction and loyalty (Eggert and Ulaga, 2002; Rabetino *et al*., 2015).

Servitization, leveraged by the use of SM technologies, has therefore increased the number of manufacturer-customer interactions, which, moreover, through service co-creation and co-production, has changed their nature from transaction to relationship-based (Oliva and Kallenberg, 2003; Wang *et al*., 2018b). Via services delivered by SM modules, manufacturers can better understand customer needs and offer personalized products that increase overall value generation (Tao and Qi, 2017; Shleha *et al*., 2022). As a result, increased customized offerings open up new markets and generate valuable and inimitable resources as a means to differentiate and generate value (Hakanen *et al*., 2017; Opazo-Basáez *et al*., 2022). Taking these arguments into consideration, we hypothesize that:

> **Hypothesis 2a**: Relational arrangement in manufacturing moderates the relationship between Smart Manufacturing and customer performance. Servitized manufacturers will therefore obtain higher customer performance from Smart Manufacturing.

2.7. Summary

The theoretical predictions outlined above are summarized in the conceptual framework shown in Figure 1. In short, this study hypothesizes that SM improves operational and customer performance. However, the effect on operational performance is greater in transnational production firms and effect on customer performance is greater in servitized (i.e., service-oriented) manufacturers.

--- Insert Figure 1 hereabouts ---

3. Methodology

3.1. Data collection

This study aims to uncover the operational and customer benefits of SM in Spanish manufacturing firms. Spain is regarded as a relevant context because it is undergoing a progressive industrial transformation (and upgrading) from labor-intensive to knowledge-intensive production: SM concept-based manufacturing (Braña, 2019; Ortín-Angel and Vendrell-Herrero, 2014). In order to identify a relevant population of Spanish manufacturing firms, the SABI database was used, which is a Bureau Van Dijk (BvD) service (http://sabi.bvdep.com) that provides accounting and financial information on representative sets of Spanish firms. The following are considered manufacturing industries - NAICS31: food, beverages and textile processing; NAICS 32: non-mineral manufacturing including wood, petroleum, plastics and chemical processing, and the pharmaceutical industry; and NAICS 33: mineral manufacturing, including hardware, vehicle, machine and turbine construction.

Firms were approached via Computer-Aided Telephone Interviewing following procedures based on the literature (Couper, 2000). The questionnaire was issued to three different innovation managers prior to implementation in order to ensure that the questions/statements were clear and easy to understand. Throughout November and December 2018, 1,761firms were contacted by phone and 438 responses received (overall answer rate of 24.87%). Among these responses, 351 were complete for the purpose of this study (valid response answer rate of 19.93%). These answer rates are common in management studies (Chidlow *et al*., 2015). To assess partial-response bias, we compared full (351) and partial (87) respondents for size and industry distribution. The *t*-tests suggested no difference between these two groups of firms, so we are confident that our results are not affected by partial respondents.

Industrial composition was similar to that of the total population (i.e., the population comprised 27% of firms in NAICS 31; 29.5% in NAICS 32 and 43.5% in NAICS 33; the sample comprised 30.1% of firms in NAICS 31; 28.3% in NAICS 32 and 41.5% in NAICS 33). The survey data was merged with the SABI database to ensure that the employee number data was completely objective.

The data and variables for non-response bias and common-method biases were tested in different ways. First, the number of employees for early and late respondents was compared. Differences between the two groups were not statistically significant at the usual levels (p-value >0.1). This suggests that there is no non-response bias in the data (Armstrong and Overton, 1977). Second, common-method bias was mitigated by ensuring that respondents were familiar with the topics under study (MacKenzie and Podsakoff, 2012); in this case, operational performance and customer performance. Third, standard validity assessment was conducted using Confirmatory Factor Analysis (CFA) as an ex-post-test of common-method bias in which variables of interest to the study were loaded onto a common- method factor (Min *et al*., 2016). The fit for the resulting model was poor (TLI = 0.636 and CFI = 0.731, acceptance range >0.900; RMSEA = 0.095, acceptance range 0.050-0.080), suggesting that there is an absence of common-method bias in the survey.

3.2. Variables

The Dependent variables are two latent variables, which are operationalized using the 5-point Likert scale items from 1= completely disagree to 5= completely agree. The first dependent variable is *Operational performance*, which is compounded by a set of eight items incorporating percent returns, percent defects, delivery speed, delivery reliability, production costs, production lead time, inventory returns and process flexibility metrics (Devaraj *et al*., 2007). Similarly, the proxy for *Customer performance* was measured using a scale incorporating customer retention, timely product delivery, customer service orientation and perceived value (Sila, 2007). The internal consistency of the scale (Hair *et al*., 1998) was measured using *Cronbach's alpha* ($\alpha_{oper\ perf} = 0.783$ and $\alpha_{cust\ perf} = 0.803$), which has solid scale reliability measures for *Composite Reliability* ($CR_{oper\ perf} = 0.833$; $CR_{cust\ perf} = 0.821$) and *Average Variance Extracted* ($AVE_{oper\ perf} = 0.531$ and $AVE_{cust\ perf} = 0.548$).

The Independent variables - in line with Tao *et al*. (2018) and Bustinza *et al*. (2021) –are a set of binary variables that measure the implementation of additional SM modules in the Manufacturing modules already implemented (e.g., MES, ERP, CRM…): the *Data driver module*, *Real-time monitoring module* and *Problem-processing module*. Considering that the independent variables are ordinal factors while the dependent variables are latent, a Multiple-Indicators Multiple-Causes (MIMIC) approach was chosen (Vendrell-Herrero *et al*., 2021b). See further details in Table 3.

--- Insert Table 3 hereabouts ---

The Moderating variables are operationalized in two dichotomies. On the one hand, geography of production splits the sample into national/local production and transnational production firms. This construct is structured according to two main questions whereby firms belonging to transnational production structures are required to respond positively to the following two questions: *Is your company part of a transnational business network*? *Does your company possess transnational production facilities*? Negative responses to these questions were considered to be of national/local supply chain structure orientation (Kano, 2018; Xing and Huang, 2021). On the other hand, the *Relational approach* splits the sample into manufacturing firms that are servitized or have service orientation. The degree of servitization was measured using Khoh *et al*. (2018); a servitization intensity index which is quantified by first calculating overall service intensity in the industry by rating the services offered by all firms, and then by individually mean-centering the overall value to measure each firm's relative servitization intensity, and each traditional or transaction-oriented manufacturing firm's relative servitization intensity. Table 4 shows how the sample is divided into these contextually-based subsamples. The mean of all the relevant variables studied and correlation matrix are shown in Table 5. As is consistent with our theoretical arguments; there exists a high correlation between SM modules and performance variables.

--- Insert Tables 4 and 5 hereabouts ---

4. Results

The MIMIC model was estimated by applying the Generalized Structural Equation Modeling (GSEM) approach using the Stata package. This model estimates the relationship between the implementation of Smart Manufacturing modules (the Data-driver, Real-time monitoring and Problem-processing modules) and Operational and Customer performance (Hypotheses H1 and H2). Table 6 shows that the model possesses high goodness-of-fit values.

--- Insert Table 6 hereabouts ---

Moderation analysis was also carried out by splitting the sample into national/local production vs. transnational production firms (H1a), and service-oriented or servitized vs. traditional or transaction-oriented firms (H2a). The results of this analysis are shown in Figure 2.

--- Insert Figure 2 hereabouts ---

As can be seen in Figure 2, all the direct coefficients behind the structural hypothesis are positive and statistically significant. This implies that Smart Manufacturing modules have a positive influence on Operational performance and Customer performance across the entire sample, which therefore upholds hypotheses H1 and H2. To be more specific, Real-time module implementation has the highest impact on both operational and customer performance [$\beta_{RTM \rightarrow Ope\ perf} = 0.442^{***}(t = 5.35;\ p < 0.001)$; $\beta_{RTM \rightarrow Cus\ perf} = 0.269^{**}(t = 4.21;\ p < 0.01$], while Problem-processing module implementation showed the lowest impact on both performance measures [$\beta_{PP \rightarrow Ope\ perf} = 0.149^{*}(t = 2.24;\ p < 0.1)$; $\beta_{PP \rightarrow Cus\ perf} = 0.192^{*}(t = 2.66;\ p < 0.1)$]. As for the moderating effects, as H1a predicts that geography of production moderates the relationship between Smart Manufacturing implementation and Operational performance ($\beta_{DD \rightarrow Ope\ perf} 0.168^{*}\ for\ Npr\ vs.\ 0.242^{*}\ for\ Tpr$; $\beta_{RTM \rightarrow Ope\ perf} 0.378^{*}\ vs.\ 0.492^{*}$, and $\beta_{PP \rightarrow Ope\ perf} 0.119^{**}\ vs.\ 0.223^{**}$), it has no moderating influence on customer performance. Conversely, as H2a suggests that relational arrangement moderates the relationship between Smart Manufacturing modules and Customer performance ($\beta_{DD \rightarrow Cus\ perf} 0.210^{**}\ for\ transaction\ vs.\ 0.304^{**}\ for\ service - oriented\ firms$; $\beta_{RTM \rightarrow Cus\ perf} 0.173^{*}\ vs.\ 0.541^{*}$, and $\beta_{PP \rightarrow Cus\ perf} 0.128^{**}\ vs.\ 0.301^{**}$), it has no moderating influence on Operational performance. These results can be interpreted in such a way that geography of production has an influence on short-term performance measures (e.g., Operational performance), while relational arrangement influences long-term performance measures (e.g., customer performance). As a whole, these results uphold H1a and H2a.

5. Discussion

This study set out to analyze the underexplored influence that the geography of production and relational arrangement of manufacturing firms may have on the relationship between SM implementation and performance. Given that big data and predictive analytics, backed up by Smart Manufacturing implementation, are increasingly identified as an essential part of corporate operational strategy (Wamba *et al*., 2020a), competitiveness (Wamba *et al*., 2020b; Kozjek *et al*., 2020) and consumer value (Akter *et al*., 2020), the positive impact on operational and customer-oriented performance by implementing such productive and analytical processes was theoretically modeled and empirically tested. This relationship was then analyzed in order to identify the potential moderating role of geography of production and relational arrangement. The findings of this study have a number of important theoretical and managerial implications for researchers and practitioners.

5.1. Implications for theory

The study was conducted employing a Multiple-Indicators Multiple-Causes model (Vendrell-Herrero *et al*., 2021b) that was estimated by Generalized Structural Equation Modeling, and a self-devised primary database comprising 351 Spanish manufacturing firms. Consequently, it was found that SM implementation has a positive effect on both operational and customer-based performance. However, the benefits of SM are unequally distributed across manufacturing firms and largely depend on their geography of production and relational arrangement with customers. It was observed that while geography of production was found to moderate the effect of SM implementation on a firm's operational performance in the case of transnational production firms, who more easily reaped productive benefits from their SM modules, the additional service orientation adopted by manufacturing firms was found to favor greater customer performance, stemming from SM implementation.

5.2. Implications for practice

The findings of this study reveal that it may be more difficult for national/local production firms to secure the operational performance benefits ensuing from SM module implementation. It could be argued that the theoretical justification behind this implication is potentially linked to the longer timescales needed by national/local production firms to reap the operational performance benefits of surmounting the complexity of the SM implementation process (Raguseo and Vitari, 2018). The absorptive capacity, organizational resources and competency developments required for the true assimilation and/or transformation of in-house processes in order to adapt to effective SM module implementation often lie beyond the boundaries of the capabilities of most nationally/locally-oriented incumbent manufacturers (Müller *et al*., 2021; Todorova and Durisin, 2007). It is therefore fair to suggest that transition towards SM—whether it be based on implementing technologies for improved manufacturing, data-analysis, real-time monitoring or problem-processing functions or not—is far more difficult, and less likely to generate the benefits hoped for, in the case of national/local production firms.

The results of this study do however imply that there may, nonetheless, be a potential solution that would enable national/local production firms to extract performance benefits more effectively from the implementation of SM technology modules. Such performance benefits do not so much relate to operational performance, but rather center on valuable customer performance achievements. National/local production firms can achieve these SM-induced performance attainments through service-orientation and greater use of servitization-oriented processes. Servitization and the use of product-service innovation by manufacturers have already been identified as a means for incumbent manufacturers to facilitate their transition toward Industry 4.0 (Vendrell-Herrero *et al*., 2021a). Greater service-orientation can offset in-house competency limitations by allowing national/local manufacturers to achieve customer-based performance through SM implementation, which can, over time, possibly bridge the competency gap hindering their access to higher operational performance gains.

Geography of production was not found to influence customer performance gains resulting from SM implementation, where service-orientation plays an important moderating role. To avoid being left behind in the current productive economy's technological transition, national/local production firms can take advantage of SM by introducing more service-augmented processes within their operations and so optimize the performance benefits that SM implementation can potentially deliver.

One advantage for manufacturers using service-orientation to reap the performance benefits arising from SM implementation is that servitization is accessible by outsourcing certain service-inducing competencies to external knowledge-intensive business service providers (KIBS) (Vaillant *et al*., 2021). National/local production firms that may otherwise lack the ability to implement effective SM processes in-house can therefore turn to servitization as a successful, eco-systemic path of transition towards Smart Manufacturing. At the meso-level, regions with rooted manufacturing traditions can steer toward the fourth industrial revolution via territorial servitization processes by using interconnections between manufacturers and KIBS so as to enable local producers, including small and micro-enterprises, to potentially use service orientation to engage in SM implementation (Lafuente *et al*., 2019). This study's findings lead us to believe that, by doing so, the constraints on the operational performance supply chain structure could possibly be counteracted, and national/local production firms given access to the customer-driven performance benefits that SM implementation can offer.

This model can also be analyzed from the perspective of transnational production firms. The results align with previous studies suggesting that transnational production firms are the firms that tend to reap the highest productivity gains from digital transformation (Opazo-Basaez *et al*., 2021). However, it is worth considering whether these firms are also the ones that benefit from building long-term relationships with consumers. On the one hand, transnational production firms tend to be less flexible (Xing and Huang, 2021), which could make customization processes difficult (Saranga *et al*., 2019). On the other hand, it is precisely the digital transformation that allows some transnational production firms to implement services and establish relationships that generate greater consumer-perceived value (Gölgeci *et al*., 2021) and, as a result, greater control of demand in the form of repeat purchases and brand loyalty (Kano, 2018). In this respect, there are success stories of transnational production firms that have managed to implement long-term relationships with their consumers in terms of both upstream (e.g., Rolls Royce) and downstream industries (e.g., Apple). These transnational production firms are a testament to the fact that our conceptual model works, and that some companies have therefore been able to obtain substantial benefits from the digital transformation, to the detriment of others. In this sense, this model implies that SM enables complex production systems (e.g., transnational) to be more productive (i.e., lower cost), and to increase the value (i.e., higher price) of complex offerings (e.g., servitization). This suggests that combining SM, transnational production and servitization results in optimal operating margins. Future econometric studies could analyze whether such a prediction is true or not.

5.3. Limitations and scope for future research

Despite the uniqueness and richness of the data used in this study, a number of limitations remain. As with all studies that are cross-sectional by nature, it does not allow for longitudinal, heterogeneity analyses. Consequently, future work based on longitudinal data would be decisive to better understand the evolution of SM implementation over time and its impact on operational and customer performance, especially where national/local production firms are involved. Recent studies using secondary data (e.g., Community Innovation Surveys and World Bank Enterprise Surveys) have solved this survey-related problem by using repeated cross-sectional approaches (Tsinopoulos *et al*., 2018; Vendrell-Herrero *et al*., 2022) This, however, is extremely costly to conduct via primary data collection. The literature, and our results, also seem to point to the fact that longer timescales are needed for national/local production firms before they can reap the full benefits of SM module implementation. Nevertheless, more comprehensive comparative studies could help ascertain whether these results can be replicated across other geographies, domains and contexts.

Finally, the conclusions reached in this study are the result of analyzing a broad spectrum of manufacturing firms. We believe that these findings and recommendations can be extended to organizations with a heterogeneous portfolio. However, future research may be able to fine tune this analysis so as to differentiate firms whose customers are end-users from firms which are primarily business-to-business, as well as firms involved in specific industries. The research objective of this study was specifically aimed at industrial firms. Nevertheless, future research could build on our findings by analyzing the performance impact of SM modules on other sectors including service-based, public and social enterprises and ventures. SM premises, technologies and tools can also be employed beyond productive sectors, opening up scope for further research into their different implications and impacts.

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TABLES

Table 1. Theoretical lenses assessing SM performance benefits

Theoretical lens	Seminal work	Generic rationale	Context-specific work	Context-specific focus
Resource-based view theory	*Barney. (1991)*	*A firm's resources are an essential factor in influencing a competitive edge.*	*Felsberger et al. (2022)*	*Examines SM impact on a firm's capabilities, competencies and market requirements in order to achieve a sustainable competitive edge.*
Socio-technical systems theory	*Appelbaum. (1997)*	*Interactional relationships between people, structures, tasks and technology produce more smoothly functioning business systems.*	*Cagliano et al. (2019)*	*Explores how SM technologies interplay with work organizations at the micro and macro-level in order to configure new socio-technical systems.*
Institutional theory	*Meyer and Rowan. (1977)*	*The performance of firms is subject to economic, social and cultural pressures arising from their own institutional environment.*	*Rodríguez-Espíndola et al. (2022)*	*Analyzes the effects market pressure, regulations and resilience have on the perceived usefulness and adoption of SM to manage risk in business operations.*
Chaos theory	*Thietart and Forgues. (1995)*	*A small change to an individual unit of a firm´s system may result in dramatic effects on the firm´s global system.*	*Hu et al. (2019)*	*Presents an efficient scheduling method in the SM environment in order to achieve overall optimization of all manufacturing tasks.*
Stakeholder theory	*Donaldson and Preston. (1995)*	*Firms are conceived to build value-adding relationships with stakeholders.*	*Gupta et al. (2019)*	*Proposes a stakeholder perspective on the use of big data analytics in order to ensure sustainable SM operations.*
Transaction-cost theory	*Williamson. (1979)*	*Firms economize on costs by selecting a form of governance that minimizes production and transaction costs.*	*Schmidt and Wagner. (2019)*	*Explores how blockchain can reduce transaction costs and enable more market-oriented governance structures for buyer-supplier transactions in SM contexts.*
Evolutionary theory	*Peters. (2009)*	*A firm´s technological capabilities are a decisive factor in explaining innovation.*	*Li et al. (2021)*	*Suggests that SM can accelerate the innovation and development of new products, and also help achieve efficient production management.*
Contingency theory	*Tosi and Slocum Jr. (1984)*	*Organizational structure and management styles are contingent on factors such as the uncertainty and instability of the environment.*	*Jang et al. (2022)*	*Demonstrates that factors such as industry type and human resource characteristics constitute key elements in SM in order to achieve better financial performance and operational efficiency.*

Information-processing theory	*Galbraith. (1973)*	*Firms can achieve superior performance by improving their information-processing capabilities and information quality.*	*Li et al. (2020)*	*Assesses how digital technologies in the SM context influence economic and environmental performance.*
Game theory	*Lee. (2008)*	*Seeks to find converging strategies for decision- makers as they attempt to maximize their own payoffs.*	*Baranwaland Vidyarthi. (2021)*	*Proposes a SM-oriented model which optimizes decision- making in the use of local and/or external computational resources, aimed at minimizing the cost of the computational services available.*

Table 2: SM modules, technologies and benefits.

Modules	Technologies	Operational benefits	Strategic benefits
Product-oriented Manufacturing module (MM)	Enterprise Resource Planning (ERP), Manufacturing Enterprise Systems (MES), Customer Relationship Management (CRM) Product Lifecycle Management (PLM).	<u>Production flexibility</u>: a set of part categories that can be produced by the manufacturing system which allows substantial set-ups, without incurring major capital equipment (Sethi and Sethi, 1990). <u>Production efficiency</u>: capacity to produce a given product using fewer resources (Thatcher and Oliver, 2001). <u>Resource efficiency</u>: ratio between added product value and the value of stressed resources used in production (Di Maio *et al*., 2017).	<u>Competitiveness</u>: a firm's ability to mobilize and efficiently employ the resources required to offer their products (Altomonte *et al*., 2011).
Data-driver module (DD)	Sensors Cloud storage	<u>Increased product development</u>: capability to transform the original products that manufacturers have in their sales portfolio into new products by capturing knowledge (Kodama, 2008).	<u>A firm's production and customer demand alignment</u>: alignment between demand fulfillment processes and demand creation (Jüttner *et al*., 2006).
Real-time Monitoring module (RTM)	Internet of Things (IoT) Industrial Internet	<u>Enhanced supply chain collaboration</u>: process of decision- making among interdependent parties involving mutual understanding and shared resources (Schrage, 1990; Stank *et al*., 2001).	<u>Business model innovation</u>: reconfiguration of current activities into new business models by adopting a novel approach to commercializing a firm's products (Girotra and Netessine, 2014).
Problem-processing module (PP)	Big data Artificial intelligence	<u>Continuous production optimization</u>: enhanced predictive approaches to detect production defects that demand prompt changes (Sjödin *et al*., 2018).	<u>Increased focus on the core business</u>: a firm's capacity to center attention on the largest, strategically most important business involving the firm (Bowen and Wiersema, 2005).

Table 3: Items for dependent and independent variables

Please indicate the extent to which you disagree/agree with the following performance indicators, where 1 = "completely disagree" and 5 = "completely agree"		
ID	ITEM	QUESTION/STATEMENT
Dependent variable 1: Operational performance (Devaraj *et al*., 2007)		
OPERF1	Returned products	The company has a low ratio of product returns arriving at the manufacturing facility (Frohlich and Westbrook, 2001).
OPERF2	Percent defects	The company has a low ratio in the number of faulty parts in total production (Frohlich and Westbrook, 2001)
OPERF3	Delivery speed	The company is punctual with regard to product delivery (Milgate, 2001).
OPERF4	Delivery reliability	The company has the capacity to fulfill delivery as assured (Milgate, 2001).
OPERF5	Production costs	All costs associated with manufacturing processes are strictly monitored (Frohlich and Westbrook, 2001).
OPERF6	Production lead time	A part is in the system for a short average time while being processed or awaiting processing (Meerkov and Yan, 2014).
OPERF7	Inventory-returns metrics	The firm has a low ratio of inventory returns arriving at the warehouse (Frohlich and Westbrook, 2001).
OPERF8	Process flexibility	The process is sufficiently flexible to accommodate changes in shipping schedules within the effective product lead time without the need to use emergency stock (Devaraj *et al*., 2007).
Dependent variable 2: Customer performance (Sila, 2007).		
CPERF1	Customer retention	The company manages to maintain the existing customer base by establishing long-term mutual benefits (Alshurideh, 2016).
CPERF2	Timely product delivery	The company is able to comply with customer delivery demands (Krause *et al*., 2007).
CPERF3	Customer-service orientation	Responding to customers is a strategic priority, and is more important than standardization (Bowen *et al*., 1989).
CPERF4	Perceived value	The company achieves a high customer-perceived value (i.e., the overall utility of the product) (Zeithaml, 1988).
Independent variable: Smart Manufacturing modules (Tao *et al*., 2018; Bustinza *et al*., 2021)		
Firms were asked whether they had adopted specific manufacturing modules, and asked to add a description for each manufacturing module.		
MM module	Product-oriented Manufacturing module	*"Does your company use a MM module which includes all traditional, supportive operations management technologies (i.e., manufacturing modules), such as CRM, ERP, MES and PLM, in order to monitor multiple manufacturing operations? Do they incorporate a variety of information systems and production resources into a man-machine-material-environment?"*

DD module	Data-driver module	*"Does your company use a DD module in the form of a cloud-based datacenter that processes explicit information and extracts recommendations to guide actions to be taken (e.g., product design, production planning and manufacturing execution)?"*
RTM module	Real-time Monitoring module	*"Does your company use an RTM module which analyzes the real-time operational status of manufacturing facilities and customer use in order to optimize operational control and customer supervision strategies?"*
PP module	Problem-processing module	*"Does your company use a PP module which identifies and predicts any problems that may arise (e.g., equipment breakdowns or quality deficiencies), diagnoses their root cause, proposes possible solutions, estimates solution effectiveness and evaluates potential impacts on other manufacturing operations or customer supervisions?"*

Table 4: Percentage of Smart Manufacturing modules according to the relevant subsample

	Geography of production		Relational arrangement		Total
	National	Transnational	Transaction-oriented (Traditional)	Service-oriented (Servitized)	Full sample
MM module	281	70	248	103	351
	100%	*100%*	*100%*	*100%*	*100%*
DD module	200	52	170	82	252
	71.17%	*74.29%*	*69.67%*	*76.64%*	*71.79%*
RTM module	151	46	130	67	197
	53.70%	*65.70%*	*52.41%*	*65.04%*	*56.10%*
PP module	90	31	77	44	121
	32.02%	*44.28%*	*31.04%*	*42.71%*	*34.47%*

Table 5. Descriptive analysis and correlations between variables

Variables	1	2	3	4	5
1. *Data-driver*	1				
2. *Real-time monitoring*	0.089	1			
3. *Problem-processing*	0.174***	0.141**	1		
4. *Operational performance*	0.129*	0.241***	0.125*	1	
5. *Customer performance*	0.154**	0.147**	0.161**	0.577***	1
Mean	0.718	0.658	0.513	3.711	3.899
Standard deviation	0.451	0.429	0.501	0.978	0.963

Note: *** p<0.001, ** p<0.01, * p<0.05

Table 6. Goodness-of-fit indicators for the constructs and relationship model

FIT TYPE	INDICATOR	NOMENCLATURE	ACCEPTANCE RANGE	VALUE
ABSOLUTE	Chi-Square Likelihood	CMIN	Significance test	169.176 (p>0.001)
	Chi-Square/DF	GFI	> 0.900	0.949
	Root Mean Square Error	RMSEA	0.050-0.080	0.058
	Root Mean Residual	RMR	< 0.050	0.032
INCREMENTAL	Compared Fit Index	CFI	> 0.900	0.979
	Normed Fit Index	NFI	> 0.900	0.963
	Tucker-Lewis Index	NNFI	> 0.900	0.949
	Adjusted Goodness-of- Fit	AGFI	> 0.900	0.946
PARSIMONY	Normed Chi-square	CMINDF	Range (1-5)	3.192

FIGURES

Figure 1: Conceptual framework

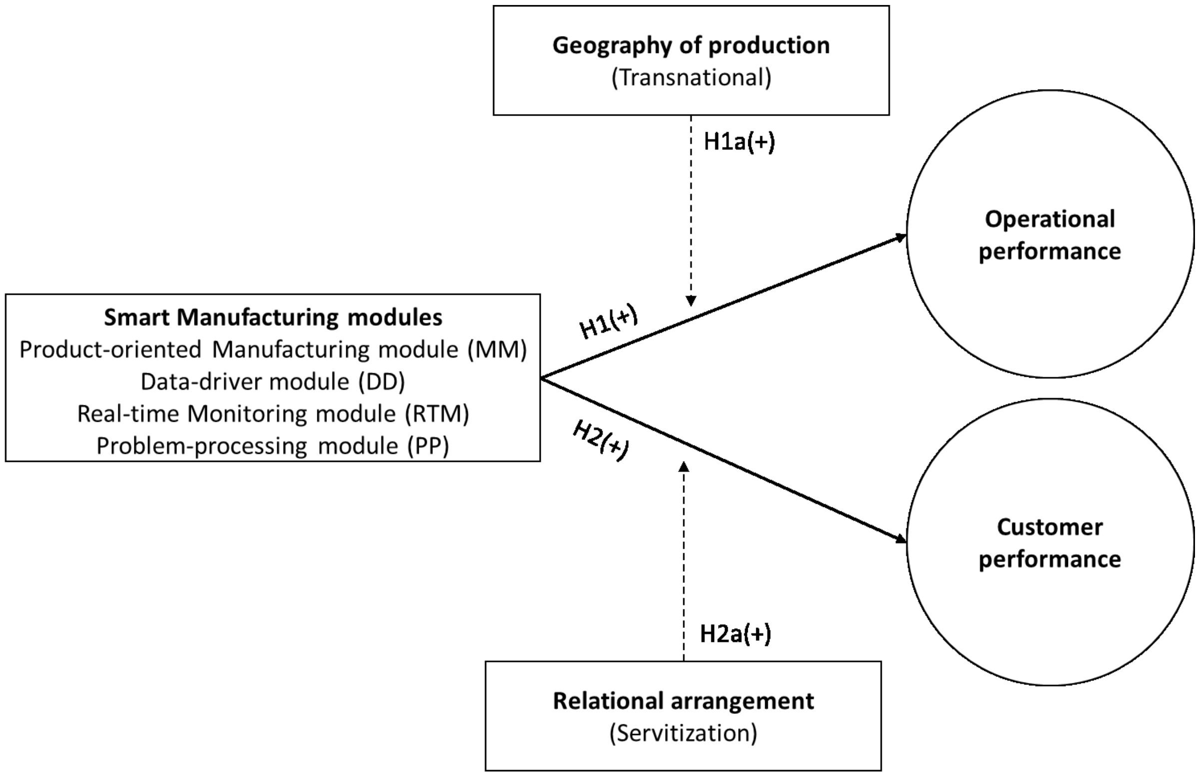

Figure 2: MIMIC model tested using GSEM