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

Marco Opazo-Basaez

*Department of Management, Deusto Business School, University of Deusto,*

*Bilbao, Spain*

Ferran Vendrell-Herrero

*Strategy Group, University of Edinburgh Business School, University of Edinburgh,*

*Edinburgh, UK*

Oscar F. Bustinza

*Department of Management I, Faculty of Economics and Business,*

*University of Granada, Granada, Spain*

Yancy Vaillant

*Department of Strategy, Entrepreneurship and Innovation, TBS Education,*

*Toulouse, France*

Josip Maric

*Department of Supply Chain and Digital Management,*

*EM Normandie Business School, M etis lab, Paris, France*

**Abstract  
Purpose** – Smart manufacturing implementation contributes to the better alignment of firms’ operation strategy and performance. Nevertheless, its effects on consumer’s perceptions and the contextualization of their performance-enhancement effects remain underexplored. This study analyzes the effect of smart manufacturing on operational and customer performance. Moreover, it studies how these relationships change depending on the firm’s supply chain structure (i.e., global value chain vs local value chain) and the adopted relational arrangement (i.e., service-oriented vs transaction-oriented manufacturers).

**Design/methodology/approach –** This research surveys 351 Spanish manufacturing firms. The theoretical framework is translated into a Multiple-Indicators Multiple-Causes model and tested through a Generalized Structural Equations Model.

**Findings –** Results support the positive effect of smart manufacturing implementation on both performance measures; while supply chain structure moderates the effect on firms’ operational performance, relational arrangement does so for customer value creation.

**Originality/value** – This work defines the benefits of smart manufacturing depending on the business context. Globalized companies will gain in operational performance whilst service-oriented manufacturers will gain in customer performance.

**Keywords** – Digital transformation, smart manufacturing, supply chain structure, relational arrangement, servitization, business performance.

**Paper type** – Research paper.

**Acknowledgments**

This research has been supported by Governments of Spain and Andalusia (Research Project A-SEJ-196-UGR20).

**1. Introduction**

Smart manufacturing (SM) is a digitally integrated manufacturing system that allows real time response to the changing conditions of production processes, customer needs and demands, as well as the business ecosystems where manufacturers operate (Kusiak, 2018). In conjunction with big data and predictive analytics, SM is rapidly and increasingly becoming a key aspect of firm operational strategy (Wamba *et al*., 2020a), and as a result, of performance (Raguseo and Vitari, 2018; Wamba *et al*., 2020b). In-fact, SM is linked to core strategic competency development, such as increased product development capabilities (Wamba *et al*., 2017), the continuous optimization of production (Gunasekaran *et al*., 2017), enhanced supply-chain collaboration and co-creation capacity (Sodero *et al*., 2019), business model innovation (Gambardella and McGahan, 2010), as well as improved solution delivery faculties (Vendrell-Herrero *et al*., 2021a). SM embraces multiple technologies (categorized as Manufacturing-based, Data-driver, Real-time monitoring, and Problem processing modules) implemented in firms and networks that are oriented to connect, monitor, and control products, services, machines, and people (Wang *et al*., 2018).

Whereas these SM induced competencies have been related to the increased operational performance of companies implanting such smart processes (Wamba *et al*., 2020b), their effects on consumer perceptions remain underexplored. Because many of the SM derived capabilities directly lead to the development and delivery of greater consumer-value (Akter *et al*., 2020), deductive reasoning would lead to believe that the implementation of such productive and analytical processes would positively impact customer performance.

Nevertheless, the impact of SM on operational and customer performance measures are likely to require contextualization. First, from an input/output perspective, supply chain structure is a key determinant of effective SM implementation (Morelli *et al*., 2020). The entry costs and learning curve involved with SM implementation are such that global value chain (GVC) that can spread such investment over greater production are favoured. Also, the added organizational and operational complexity of GVCs are more likely to see higher value-added and output that compensates the resource allocation required for adequate SM implementation (Oliveira *et al*., 2021). Similarly, from an absorptive capacity perspective, GVCs are generally characterized as having greater transformation and assimilation capacity that would likely make these more apt to better adopt and integrate SM processes (Todorova and Durisin, 2007; Müller *et al*., 2021). As such, supply chain structure is likely to moderate the relationship between SM adoption and performance, namely operational performance.

For customer performance, however, the impact of SM is much more likely to be influenced by the service orientation of the firm (Rymaszewska *et al*., 2017). SM induced servitization tends to stimulate relationship-based rather than transaction-based interactions between manufacturers and their customers (Oliva and Kallenberg, 2003). SM technologies are crucial for the proper solution delivery model that underline service-oriented firms as they allow for customised value-creation that are specifically incentive-designed to influence customer behaviour and satisfaction (Neely, 2008; Tao and Qi, 2017). Therefore, the service orientation of producers is likely to moderate the relationship between SM adoption and performance, namely customer performance.

This study aims to find out if the implementation of smart manufacturing modules is positively related to operational and customer performance, and whether the supply chain structure and the adopted relational arrangement (i.e., service-oriented vs transaction-oriented) of manufacturing companies moderate this relationship. To reach this research objective the study carries out a Multiple-Indicators Multiple-Causes model (Vendrell-Herrero *et al*., 2021b), estimated through Generalized Structural Equation Modelling, using a self-devised primary data base of 351 Spanish Manufacturing firms.

This study makes various important contributions to business analytics in supply chain performance. First, it responds to the calls made by Gölgeci *et al*. (2021) as well as Das and Dey (2021) for greater research and literature on the application of analytics and its differential impact when implemented within GVCs or in servitized contexts. Not only are SM’s different technological modules detailed in relation to their technologies as well as their potential operational and strategic benefits, but these are contextualized based specifically on the internationalization (i.e., international dispersion) of supply chains and their service-orientation. This allows the study to confirm that it is generally more difficult for firms depending on local/regional providers (i.e., local value chain—LVC) to reap the operational performance benefits of smart manufacturing module implementation. But despite the operational performance benefits being limited for domestic focused firms, servitization is a way for them to access customer performance benefits and compensate for the liabilities of reduced/shorter value chains affecting their SM implementation.

**2. Background literature and hypotheses development**

*2.1 Smart manufacturing modules*

SM is a networked paradigm that integrates several technologies such as Internet-of-Things (IoT), Big data and predictive analytics (BDPA), industrial internet, and artificial intelligence (Ren *et al*., 2019). IoT is the infrastructure that allows big data accessing and gathering through real time monitoring, while BDPA concept encompasses those problem-processing systems oriented to handle this data in terms of capturing, storing, transferring and sharing for predictive application (Gunasekaran *et al*., 2017). Artificial intelligence –another problem processing system– is behind the new smart products framework, characterized by integrating monitoring, control, optimization, and autonomous decision making (Porter and Heppelmann, 2015).

SM embraces multiple technologies implemented in firms and networks that are oriented to connect, monitor, and control products, services, machines, and people (Wang *et al*., 2018). Therefore, SM implementation is operationalized through four technological modules that operate at once, beginning from the product-oriented Manufacturing module (MM), the more traditional ones, which incorporates software as Enterprise Resource Planning (ERP), Manufacturing Enterprise Systems (MES), Customer Relationship Management (CLM), or Product Lifecycle Management (PLM) (Bustinza *et al*., 2021). From here, a Data-driver (DD) module is responsible of gathering all the information from the system, not just from the human operators and production equipment data generated on 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). DD module, operating on a cloud basis, gathers big data from MM and RTM modules, as well from the fourth module, the Problem-processing (PP) one. PP module identifies and predicts possible problems while suggesting plausible solutions that can be taken from humans or artificial intelligence. In doing so, this module estimates effectiveness, evaluates impacts on operations, support proactive maintenance, and reports actionable recommendations to MM module (Tao *et al*., 2018). The relationship between SM modules, technologies and benefits is depicted in Table 1.

--- Insert Table 1 hereabouts ---

*2.2 Smart manufacturing and operational performance*

SM potential benefits are related to reducing costs, improving operational equipment & availability, increasing operations speed, and improving product quality (Cline, 2017; Lafuente et al., 2019). The literature proposes a comprehensive set of indicators to evaluate the benefits derived from SM implementation –cost, optimized productivity, quality, integration, flexibility, and real-time diagnosis– that basically are supported by traditional performance measures –quality, cost, delivery, flexibility, operational, and strategic indicators (Shepherd and Günter, 2006; Kamble *et al*., 2020). Getting into details of the aforementioned benefits, the effects of data analysis on cost reduction, optimized productivity, and quality comes from the Second Industrial Revolution. This was where raw data was used in early statistical models for enhancing production planning, decreasing failure rates, or improving raw material consumption (Tao *et al*., 2018). Integration and flexibility were reached through applying interactive information and manufacturing technologies such as ERP or CRM to production. Real-time diagnosis was enabled by the use of IoT in manufacturing. Finally, further developments such as BDPA and Artificial Intelligence have made it possible for SM to positively influence 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 able to be produced by the manufacturing system allowing substantial setups without adding major capital equipment (Sethi and Sethi, 1990). It permits firms to compete in markets where continuous new products development is a competitive weapon. Production efficiency is related to the capacity to produce a given product with fewer resources, therefore contributing to the reduction in the number of inputs required for producing a standard output (Thatcher and Oliver, 2001). Production quality is understood as the capacity of the system to produce following previously set requirements and specifications, and according to acceptable production safety levels in term of functional safety of devices and production machines (Sethi and Sethi, 1990; Wronka, 2018). Production reliability is basically assessed as the number of defective items to the total number of produced items during a given time period. While product availability is the ratio between the actual production and the planned one, that is, it measures the system’s capacity for meeting delivery or performance demands (Meng *et al*., 2018). Finally, continuous production optimization is reached through SM by the enhanced predictive and monitoring approaches for early detection of production defects (Sjödin *et al*., 2018).

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

**Hypothesis 1**: Smart manufacturing implementation is positively related to operational performance.

*2.3 The moderating role of supply chain structure*

Supply chain structure is an important contextual variable for various reasons. Actually, the academic literature related to LVC and GVC mostly diverge. There are various differences between these types of supply chain structures. In terms of operational processes, they differ in terms of the different manufacturing practices used (Sampath and Vallejo, 2018; Keijser *et al*., 2021). These practices are related to specific manufacturers’ capabilities that allow firms to compete in an extended number of markets (Vendrell-Herrero *et al*., 2020; Opazo-Basáez *et al*., 2021). These competencies have become established processes and world-class manufacturing standards for improving operations management (Oliveira *et al*., 2021). Following these literature streams, LVCs and GVC companies differ in how they manage their operational processes (Keijser *et al*., 2021). As an example, some differences between LVCs and GVC firms in term of manufacturing practices found in the literature are related to JIT (Gereffi, 2020), TQM (Saranga *et al*., 2019; Islam and Polonsky, 2020), or lean manufacturing (Nattrass and Seekings, 2018; Cheng *et al*., 2021).

In the case of LVCs, less access to business markets, simpler operational set-ups and shorter production volumes, SM implementation may not hold enough potential merit to compensate the important entry cost and learning curves involved (Morelli *et al*., 2020). Local producers often require longer periods of time to harvest the operational performance benefits of surmounting the complex SM implementation process (Raguseo and Vitari, 2018). To reach the optimal operational performance benefits resulting from the implementation of SM modules, firms need to not only be able to effectively implement and operate these technologies and advanced tools, but they must also be able to adequately interpret the analytical intelligence generated. The organizational resource and competency developments required for proper assimilation and/or transformation of internal processes to adjust for an effective SM module implementation is often beyond the absorptive capacity and immediate capability frontier of locally-oriented incumbent manufacturers (Todorova and Durisin, 2007; Müller *et al*., 2021). The expected operational performance benefits from SM implementation may therefore be less attainable in the case of LVC structures.

Moreover, previous studies suggest that GVC companies are more likely to be confronted with coordination challenges (Opazo-Basáez *et al*., 2021) that hamper adequate strategic implementation and performance (Paolucci *et al*., 2021). The introduction of SM is a way to resolve these challenges, which due to scale implies greater production efficiency and superior performance gains.

This would suggest that the effect of SMs on operational performance is greater in GVC companies than in LVC companies. Therefore, we hypothesize that:

**Hypothesis 1a**: Supply chain structure moderates the relationship between Smart manufacturing and operational performance. Manufacturers operating in GVC will obtain higher operational performance from Smart manufacturing.

*2.4 Smart manufacturing and customer performance*

In respect of SM strategic potential benefits, literature proposes positive effects related to increased focus on the 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 firms’ skills, that can allow them to move into new markets while keeping the focus on their core business (Depecik *et al*., 2014). Through sensors, monitoring, and computational control, SM improves productivity (Wang *et al*., 2018), making the productivity growth curve concave. Business model innovation sustains the competitive strategy by better determining market segments thus allowing firms to reduce risk behind uncertain demand (Gambardella *et al*., 2010; Girotra and Netessine, 2014). By relaying on SM technologies to develop business model innovation, firms may create the commonalities needed for better serving specific market segments and, therefore, their customers (Vendrell-Herrero *et al*., 2021c). Algorithms operating under SM system are able to extract the value behind big data that is the key to improve competitiveness (Altomonte *et al*., 2011; Qi and Tao, 2018). Furthermore, SM helps to accurately understand market preferences and customers demand, the pillars of an appropriate design phase on product innovation. Finally, SM is supported by monitoring, communication, and control capabilities that create the alignment between firms and customers needed to offer a more immediate response to dynamic changing market demands (Wang *et al*., 2018). As a result, we may infer that higher interactions generate higher value creation opportunities. Taking into account these arguments, we hypothesize that:

**Hypothesis 2**: Smart manufacturing implementation is positively related to customer performance.

*2.5 The moderating role of the relational arrangement*

Servitization is a paradigm shift in manufacturing that describes manufacturers’ transformation for developing service-oriented business models that are often opened-up using digital technologies (Bustinza *et al*., 2020). The main differences that arise between traditional (i.e., transaction-oriented) manufacturing firms and servitized (i.e., service-oriented) manufacturers are generated from the fact that servitized producers focus their systems on improving the interaction between production processes and service operations (Vendrell-Herrero, *et al*., 2021b). For servitized manufacturers, organizational capabilities are underpinned by the information collected and processed from customers and a changed notion of asset management where services are specifically incentive-designed to influence on customer behaviour (Neely, 2008; Bustinza *et al.,* 2019). Furthermore, product usage training, assistance, and interaction are made possible by services developed through Smart manufacturing technologies (Tao and Qi, 2017; Ghouri *et al*., 2021), that in turn, hugely increases the producer’s interactions and relationships with customers (Rabetino *et al*., 2015).

Servitization, leveraged by the use of smart manufacturing technologies, has thus increased the number of manufacturer-customer interactions that, additionally, has changed their nature from transaction-based to relationship-based ones (Oliva and Kallenberg, 2003; Wang *et al*., 2018). Through services delivered by SM modules, manufacturers can better understand customer needs and offer personalized products that increase the overall value generation (Tao and Qi, 2017). As a result, increased customized offerings open new markets and generate valuable and inimitable resources, means for differentiation and value generation (Hakanen *et al*., 2017). Considering these arguments, we hypothesize that:

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

*2.6 Summary*

The theoretical predictions outlined above are summarized in a conceptual framework depicted in Figure 1. In sum, we hypothesize that SM improves operational and customer performance, but the effect on operational performance is stronger for GVC firms and the effect on customer performance is stronger for service-oriented (i.e., servitized) manufacturers.

--- Insert Figure 1 hereabouts ---

**3. Methodology**

*3.1 Data collection*

To test the hypotheses in this study, we collect survey data. In order to identify a relevant population of Spanish manufacturing firms we resort to the SABI database, a Bureau Van Dijk (BvD) service ([http://sabi.bvdep.com](http://sabi.bvdep.com/)), which provides accounting and financial information on a representative set of Spanish firms. Considered as manufacturing industries are NAICS31: food, beverage, and textile processing; NAICS 32: non-mineral manufacturing including wood, petroleum, plastics and chemical processes, and the pharmaceutical industry; NAICS 33: mineral manufacturing, including hardware, vehicle, machine, and turbine construction. By using a Gaussian distribution and setting up the confidence level at 95%, a representative sample needs to have at least 366 observations.[[1]](#footnote-1)

Firms were approached via Computer-Aided Telephone Interviewing, following procedures grounded on the literature (Couper, 2000). The questionnaire was issued to three different innovation managers prior to implementation to ensure that the questions were clear and easy to digest. Throughout November and December 2018, companies were contacted by phone until 438 responses were obtained with sectorial composition nearing that of the total population (i.e., population has 27% of firms in NAICS 31, 29.5% in NAICS 32 and 43.5% in NAICS 33; sample has 30.1% of firms in NAICS 31, 28.3% in NAICS 32 and 41.5% in NAICS 33). Survey data was merged with the SABI database to ensure that number of employees’ data were fully objective.

We test our data and variables for non-response bias and common method biases in various ways. First, we compare the number of employees for early and late respondents. 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, we mitigate common method bias by ensuring that respondents were familiar with the topics studied (MacKenzie and Podsakoff, 2012), in this case, operational performance and customer performance. Third, we conducted standard validity assessment through a confirmatory factor analysis (CFA) as an ex-post test of common-method bias in which variables of interest in the study were loaded onto a common method factor (Min *et al*., 2016). The fit of 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 there is an absence of common-method bias in the survey.

*3.2 Variables*

The dependant variables are two latent variables operationalised using 5-point Likert scale items from 1=disagree completely to 5=agree completely (See more details in Table 2). First dependent variable is *Operational performance*, that 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, our proxy for *Customer performance* is measured through a scale that incorporates customer retention, timely delivery of products, customer service orientation, and perceived value (Sila, 2007). The scales’ internal consistency (Hair *et al*., 1998) was measured through the *Cronbach’s alpha* ( and ), having solid scale reliability measures for *Composite Reliability* (; ), as well as for *Average Variance Extracted* ( and ).

The independent variables are – following Tao *et al*. (2018) and Bustinza *et al*. (2021) – a set of binary variables that measure the implementation of additional Smart Manufacturing modules to the already implemented Manufacturing module (e.g. MES, ERP, CRM…): *Data driver module*, *Real-time monitoring module*, and *Problem-processing module*.[[2]](#footnote-2) Considering that the independent variables are ordinal while dependant variables are latent factors, a Multiple-Indicators Multiple-Causes (MIMIC) approach is chosen (Vendrell-Herrero *et al*., 2021b).

--- Insert Table 2 hereabouts ---

The Moderating variables are operationalized in two dichotomies. On the one hand, *Supply chain structure* splits the sample into LVCs and GVC firms. We structure this construct under two main questions, thereby, firms belonging to a GVC are required to answer positively to these two questions; is your company part of a transnational business network?, does your company possess transnational production facilities?. Not responding positively to these questions is considered a domestic/local supply chain structure orientation (Kano, 2018; Xing and Huang, 2021). On the other hand, *Relational approach*, splits the sample into manufacturing firms with service-oriented or servitized–the degree of servitization was measured using Khoh *et al*. (2018) servitization`s intensity index which is quantified through, firstly calculating the overall service intensity in the industry by rating the services offered by all the firms, and then individually mean-centering this overall value to measure the relative servitization intensity for each firm, and traditional or transaction-oriented manufacturing firms. Table 3 shows how the sample is divided into these contextual based subsamples.

--- Insert Table 3 hereabouts ---

**4. Results**

MIMIC model is estimated through a Generalized Structural Equation Modelling (GSEM) approach using the Stata package. This model estimates the relationship between the implementation of key Smart manufacturing modules (Data-driver, Real-time monitoring, and Problem-processing modules) and Operational as well as Customer performance (Hypothesis H1 and H2). Moderation analysis are also carried out by splitting the sample into LVCs vs GVC firms (H1a) and servitized vs traditional firms (H2a). Results of the 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. That means that the Smart manufacturing modules have a positive influence on Operational performance and on Customer performance for the full sample, therefore supporting hypothesis H1 y H2. At a more detailed level, Real-time module implementation has the highest impact on both operational and customer performance [; ], being Problem-processing module implementation the one showing the lowest effect on both performance measures [; ]. As per the moderator effects, as H1a predicts supply chain structure moderates the relationship between Smart manufacturing implementation and Operational performance (; , and ), having no moderator influence on Customer performance. Conversely, as H2a proposes relational arrangement moderates the relationship between Smart manufacturing modules and Customer performance (; , and ), having no moderator influence on Operational performance. The results can be interpreted in the way that supply chain structure has an influence on short term performance measure (e.g., operational performance), while the relational arrangement influences on the long run performance measure (e.g., customer performance). Altogether, these results support H1a and H2a.

**5 Discussion and conclusions**

This study set out to analyse the underexplored influence that the supply chain structure and the relational arrangement of manufacturing firms may have over the relationship between the implementation of smart manufacturing and performance. Because big data and predictive analytics, supported by smart manufacturing implementation, are increasingly identified as an essential part of firm operational strategy (Wamba *et al*., 2020a), competitiveness (Wamba *et al*., 2020b; Jeble *et al*., 2020), and consumer-value (Akter *et al*., 2020), the positive impact on operational and customer-oriented performance as a result of the implementation of such productive and analytical processes was theoretically modelled and empirically tested. This relation was then analysed so as to identify the possible moderating role of supply chain structure and relational arrangement.

The study was done by carrying-out a Multiple-Indicators Multiple-Causes model (Vendrell-Herrero *et al*., 2021b), estimated through Generalized Structural Equation Modelling, using a self-devised primary data base of 351 Spanish Manufacturing firms. As a result, it was found that SM implementation has a positive effect on both operational and customer-based performance. However, the benefits of digital transformation (i.e. SM) are unequally distributed across manufacturing firms and mostly depend on their supply chain structure and relational arrangement with customers. We identify that while supply chain structure was found to moderate the effect of SM implementation on a firm’s operational performance with GVC firms more easily reaping the productive benefits from there SM modules, the added service orientation of manufacturing firms was discovered to favour greater customer performance from SM implementation.

These results appear to imply that it may be more difficult for LVCs to secure the operational performance benefits ensuing from data analytics and SM module implementation. The theoretical justification behind this implication is argued to potentially be linked to the longer time necessary for LVCs to reap the operational performance benefits of surmounting the complex SM implementation process (Raguseo and Vitari, 2018). The absorptive capacity as well as the organizational resource and competency developments required for proper assimilation and/or transformation of internal processes to adjust for an effective SM module implementation is often beyond the immediate capability frontier of most incumbent manufacturing LVCs (Müller *et al*., 2021; Todorova and Durisin, 2007). It is therefore fair to imply that the transition towards SM analytic processes -whether based on implementing technologies for improved manufacturing, data-analysis, real-time monitoring, or problem-processing functions- is more difficult and less likely to generate expected benefits in the case of LVC firms.

The study’s results do imply, however, that there may nevertheless be a potential solution that can allow LVCs to better extract performance benefits from the implementation of SM technology modules. These performance benefits are less related with operational performance, but rather centre on valuable customer performance achievements. LVCs can reach these SM induced performance attainments through service-orientation and a greater use of servitization oriented processes. Servitization and the use of product-service innovation by manufacturers has already been identified as a means for incumbent manufacturers to facilitate their transition to Industry 4.0 (Vendrell-Herrero *et al*., 2021a). Greater service-orientation can compensate for internal competency limitations by allowing LVC manufacturers to achieve customer-based performance from their SM implementation, which can over time possibly bridge the competency gap limiting their access to operation performance gains.

Supply chain structure was not found to influence the customer performance gains resulting from SM implementation, where service-orientation plays an important moderating role. To avoid being left behind of the current data-driven transition of the productive economy, LVCs can take advantage of SM to introduce greater service-augmented processes within their operations and this way optimize the performance benefits that data analytics in conjunction with SM implementation can potentially deliver.

One advantage for manufacturers of using service-orientation to reach the performance benefits coming from SM implementation is that servitization is accessible through the outsourcing of certain service-inducing competencies to external knowledge intensive business service providers (KIBS) (Vaillant *et al*., 2021). In this manner, manufacturing LVCs that may otherwise lack the ability to internally implement effective SM processes, can turn to servitization as an eco-systemic manner to successfully transition towards smart manufacturing. At the meso-level, regions with strong manufacturing traditions can set themselves on course to the fourth industrial revolution through a territorial servitization process, which uses the interconnections between manufacturers and KIBS to allow local producers, including the small and micro enterprises among them, to potentially use service orientation to engage in SM implementation (Lafuente *et al*., 2019). The findings of this study would lead to believe that doing so could possibly contrast the operational performance supply chain structure-constraints and give manufacturing LVCs access to the customer-driven performance benefits that SM implementation can offer.

The model can also be analyzed from the perspective of the globalized company. Our results are aligned with previous studies that propose that global companies are those that will possess the highest productivity gains from digital transformation (Opazo-Basaez *et al*., 2021). However, it is worth considering whether these companies can also be those that benefit from building long-term relationships with consumers. On the one hand, the global company tends to be less flexible (Xing and Huang, 2021), which would make customization processes difficult (Saranga *et al*., 2019). On the other hand, it is precisely the digital transformation that allows some global companies to implement services and establish relationships that achieve a greater generation of consumer perceived value (Gölgeci *et al*., 2021), and as a result greater demand control in the form of repeat purchases and brand loyalty (Kano, 2018). In this sense, there are success stories of global companies that have managed to implement long-term relationships with their consumers both in terms of upstream industries (e.g. Rolls Royce) and downstream industries (e.g. Apple). These global companies are a testament that our conceptual model works and that therefore some companies have been able to obtain a great benefits from the digital transformation to the detriment of others. In this sense, our model tells us that SM enables complex production systems (e.g. GVC) to be more productive (i.e. lower cost) and to increase the value (i.e. higher price) of complex offerings (e.g. servitization). This implies that the combination of SM, GVC and servitization would result in an optimal operating margin. Future econometric studies may analyse whether our prediction is true or not.

Although the uniqueness and richness of the data used in this study, a number of limitations remain. As with all studies of a cross-sectional nature, the study 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 SM implementation and their impact over operational and customer performance, especially when LVC manufacturers are involved. The literature, and our results, seem to point towards longer periods required for LVC firms before they can harvest the full benefits of their SM module implementation.

Finally, the conclusions generated in this study are the result of the analysis of a large spectrum of manufacturing firms. We believe that our findings and recommendations can be extended to organizations with a heterogeneous portfolio, however, future research could fine tune the current analysis in order to distinguish between firms whose customers are end users and firms that have a primarily Business-to-Business nature, as well as companies involved in specific industries. Our study’s research objective was specifically aimed towards industrial companies, but future research could build on our findings to analysis the performance impact of predictive analytics modules in other sectors including service-based, public as well as socially aimed organizations and ventures. Smart manufacturing premises, technologies and tools can be implemented beyond the productive sectors, opening-up a scope for further research into the differentiated implications and impacts of doing so.

**References**

Akter, S., Gunasekaran, A., Wamba, S. F., Babu, M. M., and Hani, U. (2020), “Reshaping competitive advantages with analytics capabilities in service systems”, *Technological Forecasting and Social Change*, In press.

Alshurideh, M. T. (2016), “Is customer retention beneficial for customers: A conceptual background”, *Journal of Research in Marketing*, Vol. 5 No. 3, pp. 382-389.

Altomonte, C., Barba Navaretti, G., Di Mauro, F., and Ottaviano, G. (2011), “Assessing competitiveness: How firm-level data can help”, Bruegel Policy Contribution.

Armstrong, J. S., and Overton, T. S. (1977), “Estimating nonresponse bias in mail surveys”, *Journal of marketing research*, Vol. 14 No. 3, pp. 396-402.

Belhadi, A., Kamble, S., Gunasekaran, A. and Mani, V. (2021), "Analyzing the mediating role of organizational ambidexterity and digital business transformation on industry 4.0 capabilities and sustainable supply chain performance", *Supply Chain Management*, In press.

Bowen, D. E., Siehl, C., and Schneider, B. (1989), “A framework for analyzing customer service orientations in manufacturing”, *Academy of Management Review*, Vol. 14 No. 1, pp. 75-95.

Bowen, H.P., and Wiersema, M F. (2005), “Foreign-based competition and corporate diversification strategy”, *Strategic Management Journal, Vol. 26 No.* 12, pp. 1153-1171.

Bustinza, O. F., Gomes, E., Vendrell‐Herrero, F., and Baines, T. (2019), “Product–service innovation and performance: The role of collaborative partnerships and R&D intensity”, *R&D Management*, Vol. 49 No. 1, pp. 33-45.

Bustinza, O. F., Opazo-Basaez, M., and Tarba, S. (2021), “Exploring the interplay between Smart Manufacturing and KIBS firms in configuring product-service innovation performance”, *Technovation*, In press.

Bustinza, O. F., Vendrell-Herrero, F., and Gomes, E. (2020), “Unpacking the effect of strategic ambidexterity on performance: A cross-country comparison of MMNEs developing product-service innovation”, *International Business Review*, Vol. 29 No. 6, p. 101569.

Cheng, Y., Fredriksson, A. and Fleury, A. (2021), "Rethinking international manufacturing in times of global turbulence", *Journal of Manufacturing Technology Management*, Vol. 32 No. 6, pp. 1113-1120.

Cline, G. (2017), “*Industry 4.0 and Industrial IoT in manufacturing: A sneak peek”,* OpsPro Essentials, Aberdeen.

Couper, M. P. (2000), “Web surveys: A review of issues and approaches”, *The Public Opinion Quarterly*, Vol. 64 No. 4, pp. 464-494.

Das, A. and Dey, S. (2021), “Global manufacturing value networks: assessing the critical roles of platform ecosystems and Industry 4.0”, *Journal of Manufacturing Technology Management*, Vol. 32 No. 6, pp. 1290-1311.

Depecik, B., van Everdingen, Y. M., and van Bruggen, G. H. (2014), “Firm value effects of global, regional, and local brand divestments in core and non‐core businesses”, *Global Strategy Journal*, Vol. 4 No. 2, pp. 143-160.

Devaraj, S., Krajewski, L., and Wei, J. C. (2007), “Impact of eBusiness technologies on operational performance: The role of production information integration in the supply chain”, *Journal of Operations Management*, Vol. 25 No. 6, pp. 1199-1216.

Di Maio, F., Rem, P. C., Baldé, K., and Polder, M. (2017), “Measuring resource efficiency and circular economy: A market value approach”, *Resources, Conservation and Recycling*, Vol. 122, pp. 163-171.

Fay, M., and Kazantsev, N. (2018), “When smart gets smarter: How big data analytics creates business value in smart manufacturing”, *Proceedings ICIS*, San Francisco.

Frohlich, M. T., and Westbrook, R. (2001), “Arcs of integration: An international study of supply chain strategies”, *Journal of Operations Management*, Vol. 19 No. 2, pp. 185-200.

Gambardella, A., and McGahan, A. M. (2010), “Business-model innovation: General purpose technologies and their implications for industry structure”, *Long Range Planning*, Vol. 43 Nos 2-3, pp. 262-271.

Geißler, A., Häckel, B., Übelhör, J., and Voit, C. (2019), “Structuring the anticipated benefits of the fourth industrial revolution”, *New Frontiers in Digital Convergence,* AMCIS 2019 Conference, Cancun (Mexico)

Gereffi, G. (2020), “What does the COVID-19 pandemic teach us about global value chains? The case of medical supplies”, *Journal of International Business Policy*, Vol. 3 No. 3, pp. 287-301.

Ghouri, A. M., Mani, V., Jiao, Z., Venkatesh, V. G., Shi, Y., and Kamble, S. S. (2021), “An empirical study of real-time information-receiving using industry 4.0 technologies in downstream operations”, *Technological Forecasting and Social Change*, doi: 10.1016/j.techfore.2020.120551.

Girotra, K., and Netessine, S. (2014), “Four paths to business model innovation”, *Harvard Business Review*, Vol. 92 No. 7, pp. 96-103.

Gölgeci, I., Gligor, D.M., Lacka, E. and Raja, J.Z. (2021), "Understanding the influence of servitization on global value chains: a conceptual framework", *International Journal of Operations & Production Management*, Vol. 41 No. 5, pp. 645-667.

Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B., and Akter, S. (2017), “Big data and predictive analytics for supply chain and organizational performance”, *Journal of Business Research,* Vol. 70, pp. 308-317.

Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E. and Tatham, R.L. (1998), “Multivariate Data Analysis”, Vol. 5, Prentice Hall, Upper Saddle River, NJ.

Hakanen, T., Helander, N., and Valkokari, K. (2017), “Servitization in global business-to-business distribution: The central activities of manufacturers”, *Industrial Marketing Management*, Vol. 63, pp. 167-178.

Islam, M. T., and Polonsky, M. J. (2020), “Validating scales for economic upgrading in global value chains and assessing the impact of upgrading on supplier firms’ performance”, *Journal of Business Research*, Vol. 110, pp. 144-159.

Jeble, S., Kumari, S., Venkatesh, V.G. and Singh, M. (2020), "Influence of big data and predictive analytics and social capital on performance of humanitarian supply chain: Developing framework and future research directions", *Benchmarking: An International Journal*, Vol. 27 No. 2, pp. 606-633.

Jüttner, U., Godsell, J., and Christopher, M. G. (2006), “Demand chain alignment competence—delivering value through product life cycle management”, *Industrial marketing management*, Vol. 35 No. 8, pp. 989-1001.

Kamble, S. S., Gunasekaran, A., Ghadge, A., and Raut, R. (2020), “A performance measurement system for industry 4.0 enabled smart manufacturing system in SMMEs: A review and empirical investigation”, *International Journal of Production Economics*, In press.

Kano, L. (2018), “Global value chain governance: A relational perspective”, *Journal of International Business Studies*, Vol. 49 No. 6, pp. 684-705.

Keijser, C., Belderbos, R., and Goedhuys, M. (2021), “Governance and learning in global, regional, and local value chains: The IT enabled services industry in South Africa”, *World Development*, doi: 10.1016/j.worlddev.2021.105398.

Kodama, T. (2008), “The role of intermediation and absorptive capacity in facilitating university–industry linkages: An empirical study of TAMA in Japan”, *Research Policy*, Vol. 37 No. 8, pp. 1224-1240.

Kroh, J., Luetjen, H., Globocnik, D., and Schultz, C. (2018), “Use and efficacy of information technology in innovation processes: The specific role of servitization”, *Journal of Product Innovation Management*, Vol. 35 No. 5, pp. 720-741.

Kusiak, A. (2018), “Smart manufacturing”, International Journal of Production Research, Vol. 56 Nos 1-2, pp. 508-517.

Lafuente, E., Vaillant, Y., and Vendrell-Herrero, F. (2019), “Territorial servitization and the manufacturing renaissance in knowledge-based economies”, *Regional Studies,* Vol. 53 No. 3, pp. 313-319.

Lee, J., Lapira, E., Bagheri, B., and Kao, H. A. (2013), “Recent advances and trends in predictive manufacturing systems in big data environment”, *Manufacturing Letters*, Vol. 1 No. 1, pp. 38-41.

MacKenzie, S. B., and Podsakoff, P. M. (2012), “Common method bias in marketing: Causes, mechanisms, and procedural remedies”, *Journal of retailing*, Vol. 88 No. 4, pp. 542-555.

Meerkov, S. M., and Yan, C. B. (2014), “Production lead time in serial lines: Evaluation, analysis, and control”, *IEEE Transactions on Automation Science and Engineering*, Vol. *13 No.* 2, pp. 663-675.

Meng, H., Kloul, L., and Rauzy, A. (2018), “Production availability analysis of Floating Production Storage and Offloading (FPSO) systems”, *Applied Ocean Research*, Vol. 74, pp. 117-126.

Milgate, M. (2001), “Supply chain complexity and delivery performance: An international exploratory study”, *Supply Chain Management: An International Journal,* Vol. 6 No. 3, pp. 106-118.

Min, H., Park, J., and Kim, H. J. (2016), “Common method bias in hospitality research: A critical review of literature and an empirical study”, *International Journal of Hospitality Management*, Vol. 56, pp. 126-135.

Morelli, G., Pozzi, C., and Gurrieri, A. R. (2020), “Industry 4.0 and the Global Digitalised Production. Structural Changes in Manufacturing”, *In Digital Business Transformation* (pp. 187-204). Springer, Cham.

Müller, J.M., Buliga, O. and Voigt, K.I. (2021), “The role of absorptive capacity and innovation strategy in the design of industry 4.0 business Models-A comparison between SMEs and large enterprises”, *European Management Journal*, In press.

Nattrass, N. and Seekings, J. (2018), “Trajectories of development and the global clothing industry”, *Competition and Change*, Vol. 22 No. 3, pp. 274-292.

Neely, A. (2008), “Exploring the financial consequences of the servitization of manufacturing”, *Operations Management Research*, Vol. 1 No. 2, pp. 103-118.

Oliva, R., and Kallenberg, R. (2003), “Managing the transition from products to services”, *International Journal of Service Industry Management,* Vol. 14 No. 2, pp. 160-172.

Oliveira, L., Fleury, A., and Fleury, M. T. (2021), “Digital power: Value chain upgrading in an age of digitization”, *International Business Review*, doi: 10.1016/j.ibusrev.2021.101850.

Opazo-Basáez, M., Vendrell-Herrero, F., Bustinza, O.F. and Marić, J. (2021), "Global value chain breadth and firm productivity: the enhancing effect of Industry 4.0", *Journal of Manufacturing Technology Management*, doi: 10.1108/JMTM-12-2020-0498.

Paolucci, E., Pessot, E. and Ricci, R. (2021), "The interplay between digital transformation and governance mechanisms in supply chains: evidence from the Italian automotive industry", *International Journal of Operations & Production Management*, Vol. 41 No. 7, pp. 1119-1144.

Porter, M. E., and Heppelmann, J. E. (2015), “How smart, connected products are transforming companies”, *Harvard business review*, Vol. 93 No. 10, pp. 96-114.

Qi, Q. and Tao, F. (2018), “Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison”, *IEEE Access*, Vol. 6, pp. 3585-3593.

Rabetino, R., Kohtamäki, M., Lehtonen, H., and Kostama, H. (2015), “Developing the concept of life-cycle service offering”, *Industrial Marketing Management*, Vol. 49, pp. 53-66.

Raguseo, E. and Vitari, C. (2018), “Investments in big data analytics and firm performance: an empirical investigation of direct and mediating effects”, *International Journal of Production Research*, Vol. 56 No. 15, pp. 1-16.

Ren, S., Zhang, Y., Liu, Y., Sakao, T., Huisingh, D., and Almeida, C. M. (2019), “A comprehensive review of big data analytics throughout product lifecycle to support sustainable smart manufacturing: a framework, challenges and future research directions”, *Journal of Cleaner Production*, Vol. 210, pp. 1343-1365.

Rymaszewska, A., Helo, P., and Gunasekaran, A. (2017), “IoT powered servitization of manufacturing: An exploratory case study”, *International Journal of Production Economics*, Vol. 192, pp. 92-105.

Sampath, P. G., and Vallejo, B. (2018), “Trade, global value chains and upgrading: what, when and how?”, *The European Journal of Development Research*, Vol. 30 No. 3, pp. 481-504.

Saranga, H., Schotter, A. P., and Mudambi, R. (2019), “The double helix effect: Catch-up and local-foreign co-evolution in the Indian and Chinese automotive industries”, *International Business Review*, doi.org/10.1016/j.ibusrev.2018.03.010.

Schrage, M. (1990), Shared Minds: The New Technologies of Collaboration, Random House, New York, NY.

Sethi, A. K., and Sethi, S. P. (1990), “Flexibility in manufacturing: a survey”, *International Journal of Flexible Manufacturing Systems*, Vol. 2 No. 4, pp. 289-328.

Shepherd, C., and Günter, H. (2006), “Measuring SC performance: Current research and future directions”, *International Journal of Productivity and Performance Management, Vol. 55 No.* 3, pp. 242-258.

Sila, I. (2007), “Examining the effects of contextual factors on TQM and performance through the lens of organizational theories: An empirical study”, *Journal of Operations Management*, Vol. 25 No. 1, pp. 83-109.

Sjödin, D. R., Parida, V., Leksell, M., and Petrovic, A. (2018), “Smart factory implementation and process innovation: A preliminary maturity model for leveraging digitalization in manufacturing”, *Research-Technology Management*, Vol. 61 No. 5, pp. 22-31.

Sodero, A., Jin, Y. H., and Barratt, M. (2019), “The social process of Big Data and predictive analytics use for logistics and supply chain management”, *International Journal of Physical Distribution & Logistics Management*, Vol. 49 No.7, pp. 709-726.

Stank, T. P., Keller, S. B., and Daugherty, P. J. (2001), “Supply chain collaboration and logistical service performance”, *Journal of Business Logistics*, Vol. 22 No. 1, pp. 29-48.

Tao, F., and Qi, Q. (2017), “New IT driven service-oriented smart manufacturing: framework and characteristics”, *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, Vol. 49 No. 1, pp. 81-91.

Tao, F., Cheng, Y., Zhang, L., and Nee, A. Y. (2017), “Advanced manufacturing systems: Socialization characteristics and trends2, *Journal of Intelligent Manufacturing, Vol. 28 No.* 5, pp. 1079-1094.

Tao, F., Qi, Q., Liu, A., and Kusiak, A. (2018), “Data-driven smart manufacturing”, *Journal of Manufacturing Systems,* Vol. 48, pp. 157-169.

Thatcher, M. E., & Oliver, J. R. (2001), “The impact of technology investments on a firm’s production efficiency, product quality, and productivity”, *Journal of Management Information Systems*, Vol. 18 No. 2, pp. 17-45.

Todorova, G., and Durisin, B. (2007), “Absorptive capacity: Valuing a reconceptualization”, *The Academy of Management Review,* Vol. 32 No. 3, pp. 774-786.

Vaillant, Y., Lafuente, E., Horváth, K. and Vendrell-Herrero, F. (2021), “Regions on course for the fourth industrial revolution: the role of a strong indigenous T-KIBS sector”, *Regional Studies*, doi: 10.1080/00343404.2021.1899157.

Vendrell-Herrero, F., Bustinza, O. F., and Opazo-Basaez, M. (2021b), “Information technologies and product-service innovation: The moderating role of service R&D team structure”, *Journal of Business Research,* Vol. 128, pp. 673-687.

Vendrell-Herrero, F., Bustinza, O. F., and Vaillant, Y. (2021c), “Adoption and optimal configuration of smart products: The role of firm internationalization and offer hybridization”, *Industrial Marketing Management*, Vol. 95, pp. 41-53.

Vendrell-Herrero, F., Darko, C. K., and Ghauri, P. (2020), “Knowledge management competences, exporting and productivity: uncovering African paradoxes”, *Journal of Knowledge Management*, Vol. 24 No. 1, pp. 81-104.

Vendrell-Herrero, F., Vaillant, Y., Bustinza, O. F., and Lafuente, E. (2021a), “Product lifespan: The missing link in servitization”, *Production Planning & Control*, pp. 1-17.

Wamba, S. F., Bawack, R. E., Guthrie, C., Queiroz, M. M., and Carillo, K. D. A. (2020b), “Are we preparing for a good AI society? A bibliometric review and research agenda”, *Technological Forecasting and Social Change*, In press.

Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J. F., Dubey, R., and Childe, S. J. (2017), “Big data analytics and firm performance: Effects of dynamic capabilities”, *Journal of Business Research*, Vol. *70*, pp. 356-365.

Wamba, S. F., Queiroz, M. M., Wu, L., and Sivarajah, U. (2020a), “Big data analytics-enabled sensing capability and organizational outcomes: Assessing the mediating effects of business analytics culture”, *Annals of Operations Research*, pp. 1-20.

Wang, B., Kang, Y., Childerhouse, P. and Huo, B. (2018), "Service supply chain integration: the role of interpersonal relationships", *Industrial Management & Data Systems*, Vol. 118 No. 4, pp. 828-849.

Wang, J., Ma, Y., Zhang, L., Gao, R. X., and Wu, D. (2018), “Deep learning for smart manufacturing: Methods and applications”, *Journal of Manufacturing Systems*,Vol. 48, pp. 144-156.

Wellener, P., Shepley, S., Dollar, B., Laaper, S., Ashton, H., and Beckoff, D. (2019), “Manufacturing goes digital: Smart factories have the potential to spark labor productivity”, *Deloitte and MAPI Smart Factory Study*. Available at https://www2.deloitte.com/us/en/insights/industry/manufacturing/driving-value-smart-factory-technologies.html

Wronka, A. (2018), “Multi-dimensionality of safety of a production process”, *Enterprise and Competitive Environment March*, 21st International Scientific Conference, Brno, Czech Republic.

Xing, Y., and Huang, S. (2021), “Value Captured by China in the Smartphone GVC A Tale of Three Smartphone Handsets”, *Structural Change and Economic Dynamics*, In press.

Zeithaml, V. A. (1988), “Consumer perceptions of price, quality, and value: a means-end model and synthesis of evidence”, *Journal of Marketing*, Vol. 52 No. 3, pp. 2-22.

*TABLES*

**Table 1:** 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 (CLM)  Product Lifecycle Management (PLM). | Production flexibility: set of part categories able to be produced by the manufacturing system that allow substantial setups without adding major capital equipment (Sethi and Sethi, 1990)  Production efficiency: capacity to produce a given product with fewer resources (Thatcher and Oliver, 2001)  Resource efficiency: ratio between added product value and the value of stressed resources used in production (Di Maio *et al*., 2017) | Competitiveness: firms’ ability to mobilize and efficiently employ the resources required to offer their products (Altomonte *et al*., 2011) |
| Data-driver (DD) | Sensors  Cloud storage | Increased product developing: capability of transforming the original products that manufacturers have in their sales portfolio into new products by capturing knowledge (Kodama, 2008) | Firms’ production and customer demand alignment: integration between demand fulfilment processes and demand creation (Jüttner *et al*., 2006) |
| Real-time monitoring (RTM) | Internet of Things (IoT)  Industrial Internet | Enhanced supply chain collaboration: process of decision making among interdependent parties with mutual understanding and shared resources (Schrage, 1990; Stank *et al*., 2001). | Business models innovation: reconfiguration of current activities into new business models by adopting a novel approach to commercializing firms’ products (Girotra and Netessine, 2014). |
| Problem-processing (PP) | Big data  Artificial intelligence | Production continuous optimization: enhanced predictive approaches for detecting production defects and demand changes sooner (Sjödin *et al*., 2018). | Increased focus on the core business: firm capacity to centre attention on the largest, strategically most important business of the firm (Bowen and Wiersema, 2005) |

*Source: Author’s own elaboration*

**Table 2:** Items for dependent variables

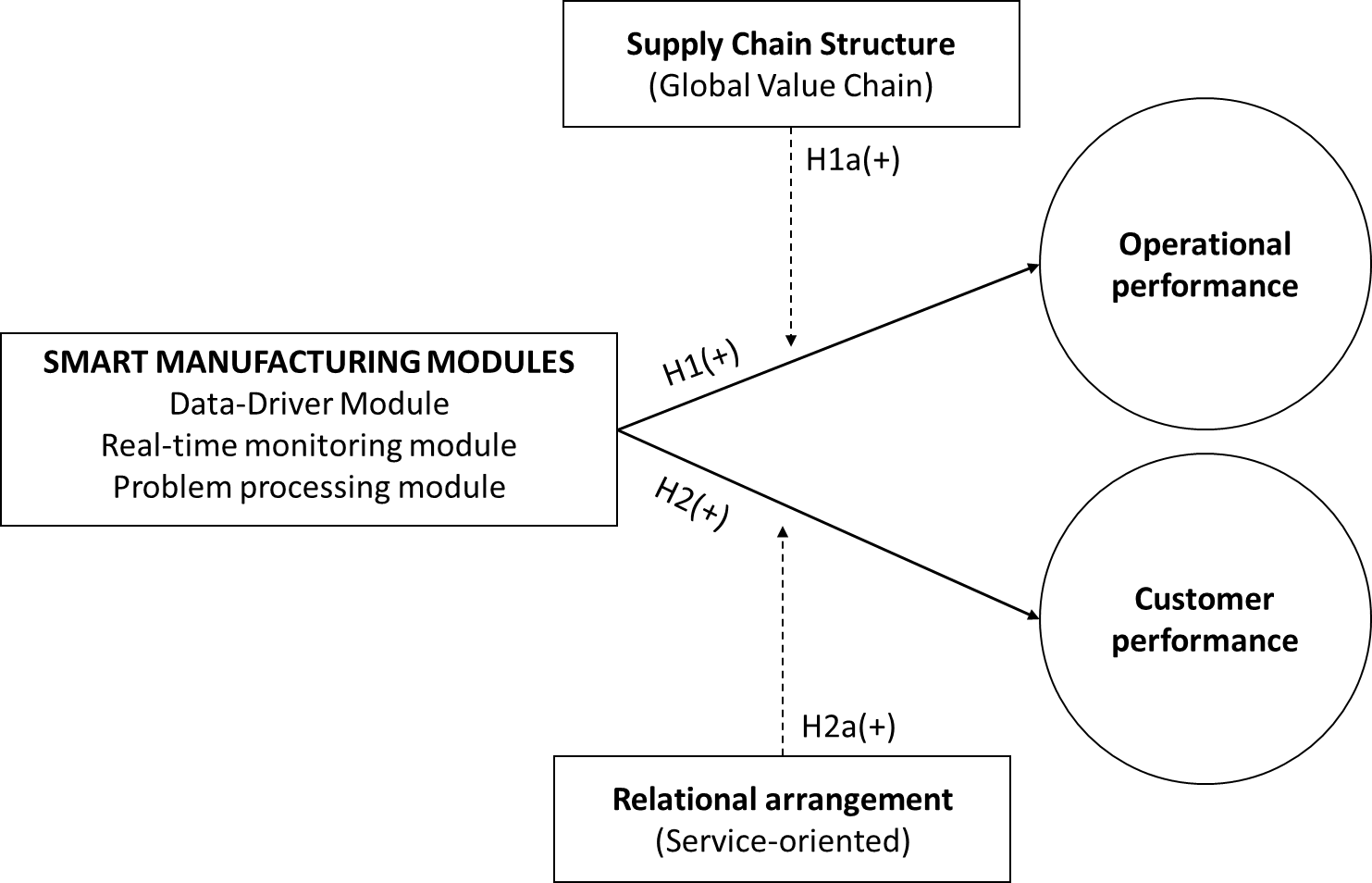
|  |  |  |
| --- | --- | --- |
| Please indicate the extent to which you disagree/agree with the following performance indicators, where 1 = “completely disagree” and 5 = “completely agree” | | |
| ID | ITEM | QUESTION |
| **Dependent variable 1: Operational performance (Devaraj et al., 2007)** | | |
| OPERF1 | Returned products | The company has a low ratio of the returns of products to the manufacturing facility (Frohlich and Westbrook, 2001) |
| OPERF2 | Percent defects | The company has a low ratio of the number of defects of parts within the total production (Frohlich and Westbrook, 2001) |
| OPERF3 | Delivery speed | The company has timeliness in the responsiveness to deliver a product (Milgate, 2001) |
| OPERF4 | Delivery reliability | The company has the capacity to fulfil the delivery as promised (Milgate, 2001) |
| OPERF5 | Production costs | All the costs associated with the manufacturing processes are strictly controlled (Frohlich and Westbrook, 2001) |
| OPERF6 | Production lead time | Low average time a part spends in the system, being processed or waiting for processing (Meerkov and Yan, 2014) |
| OPERF7 | Inventory returns metrics | The company has a low ratio of the returns of inventories to the warehouse (Frohlich and Westbrook, 2001) |
| OPERF8 | Process flexibility | There is flexibility of the process to accommodate changes to shipping schedules within the effective lead time of the product without the use of safety stock (Devaraj *et al*., 2007) |
| **Dependent variable 2: Customer performance (Sila, 2007)** | | |
| CPERF1 | Customer retention | The company achieves maintenance of the existing customer base by establishing mutual long-term benefits (Alshurideh, 2016) |
| CPERF2 | Timely delivery of products | The company has the capacity to fulfil when the customers want their deliveries to arrive |
| CPERF3 | Customer service orientation | Customer responsiveness is a strategic priority more important than standardization (Bowen *et al*., 1989) |
| CPERF4 | Perceived value | The company achieves a high customer perceived value (i.e., the overall utility received from products) (Zeithaml, 1988) |

**Table 3:** Percentage of Smart manufacturing modules by relevant subsamples

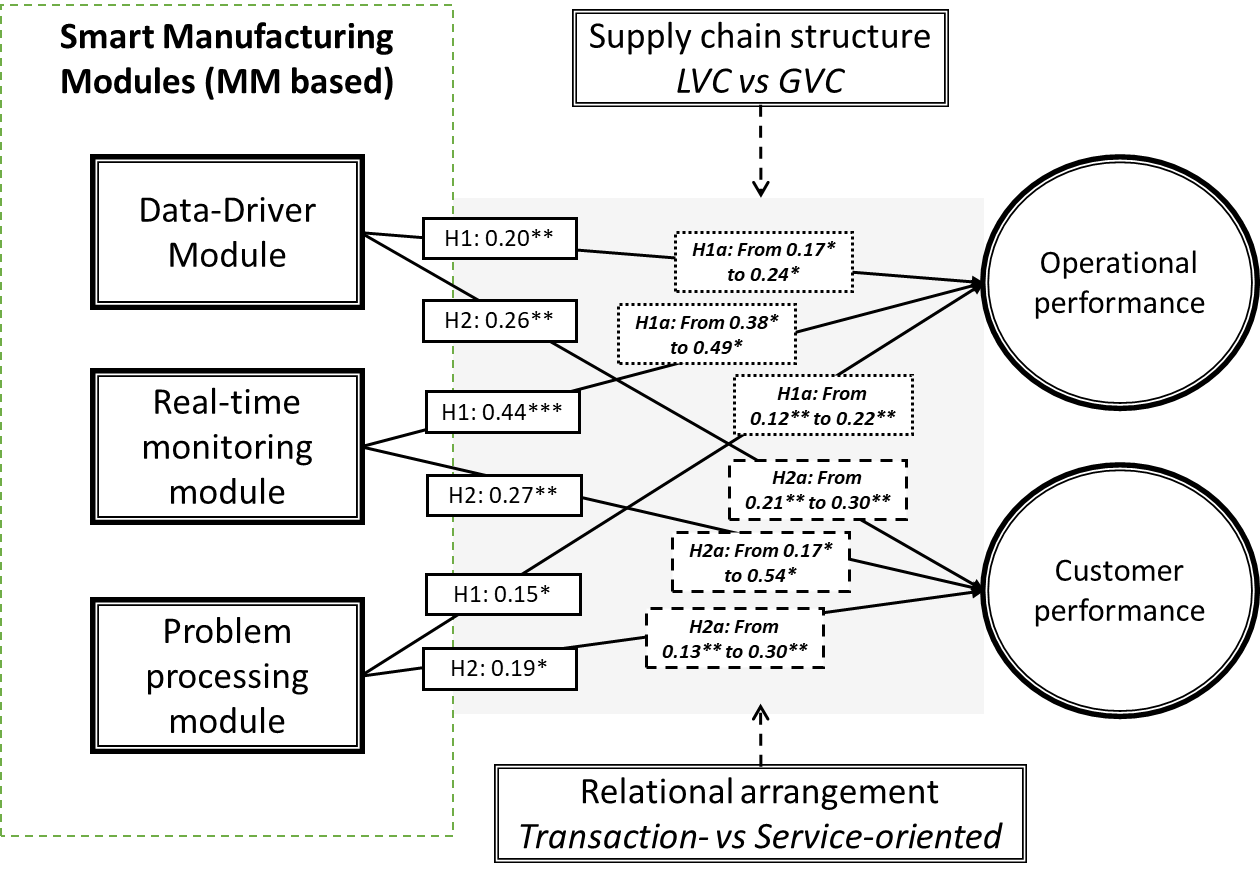
|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Supply chain structure | | Relational arrangement | | Total |
|  | LVC | GVC | Transaction-oriented  (Traditional) | Service-oriented  (Servitized) | Full sample |
| MM module | 281 | 70 | 248 | 103 | 351 |
|  | *100%* | *100%* | *100%* | *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%* |

*FIGURES*

**Figure 1**: Conceptual framework



**Figure 2**: MIMIC model tested through GSEM



1. , where *n* is the target sample size, *N* is the population (*N*=7,552), *Z*=+/-1.96 (95% confidence level), *e* is the margin of error (*e*=5%), and *p* is a realistic estimate of desired probability (*p*=0.50). [↑](#footnote-ref-1)
2. We asked firms questions of the form “Have your firm introduced [add specific manufacturing module]?”, adding definition and example for each manufacturing module. [↑](#footnote-ref-2)