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The impact of online sales configurators on mass-customization capability: the role of complementarities with product modularity and product knowledge absorption from customers

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Contents

List of figures

List of tables

List of abbreviations

Abbreviation	Full name
AVE	average variance extracted
CFA	confirmatory factor analysis
CFI	comparative-fit index
CMB	common method bias
CR	composite reliability
HPM	high-performance manufacturing
IFI	incremental-fit index
M	mean value
MCC	mass-customization capability
OSC	online sales configurator
PKAC	product knowledge absorption from customers
PM	product modularity
RMSEA	root mean square error of approximation
SD	standard deviation
SEM	structural equation modeling
SMC	Squared multiple correlation
TLI	Tucker-Lewis coefficient

Abstract

Mass-customization capability (MCC) denotes an organization's ability to provide customized products and services that fulfil each customer's idiosyncratic needs without considerable trade-offs in cost, delivery, and quality. The existing literature recognizes that online sales configurators (OSCs), which are software applications that enable customers to self-customize their product solutions online, play an important role in MCC development. However, large-scale empirical studies focused on the impact of using an OSC on MCC are still missing. The present research starts to narrow this gap by conceptually and empirically examining not only the main effect of OSC use on MCC but also the impact of the interplay of OSC use and other two MCC enablers that prior research has related to OSCs and to OSC effectiveness in improving MCC: product modularity (PM) and product knowledge absorption from customers (PKAC). The central argument of this research is that the OSC use, PM, and PKAC forms a three-way system of complements resulting in higher MCC levels. To test for this three-way complementarity hypothesis, three different approaches developed in the relevant literature were triangulated. On the whole, the results obtained from the application of all these approaches converge in supporting the hypothesized three-way complementarity between OSC use, PM, and PKAC. The contributions of this finding to the MCC literature as well as to managerial practice are discussed. Finally, the limitations of the present work, along with the related opportunities for further research, are outlined.

Sommario

La capacità di mass customization (MCC) indica la capacità di un'organizzazione di fornire prodotti e servizi personalizzati in grado di soddisfare le esigenze idiosincratiche di ciascun cliente senza notevoli compromessi in termini di costi, tempi e qualità. La letteratura esistente riconosce che i configuratori commerciali online (OSC), definiti come applicazioni software che consentono ai clienti di personalizzare le proprie soluzioni di prodotto online, svolgono un ruolo importante nello sviluppo della MCC. Tuttavia, mancano ancora studi empirici su larga scala incentrati sull'effetto dell'uso di un OSC sulla MCC. La presente ricerca inizia a colmare questa lacuna esaminando, concettualmente ed empiricamente, non solo il main effect dell'uso dell'OSC sulla MCC, ma anche l'impatto dell'uso congiunto di un OSC e di altri due enabler della MCC che la ricerca precedente ha associato agli OSC e alla loro efficacia ai fini del miglioramento della MCC: la modularità del prodotto (PM) e l'assorbimento di conoscenza sul prodotto dai clienti (PKAC). La tesi fondamentale di questa ricerca è che l'uso di un OSC, la PM e la PKAC costituiscono un sistema di pratiche organizzative complementari che produce livelli superiori di MCC. Per testare questa ipotesi di complementarità a tre vie si sono triangolati tre diversi approcci sviluppati in letteratura. Nel complesso, i risultati derivanti dall'applicazione di tutti e tre gli approcci convergono nel supportare l'ipotesi di complementarità a tre vie tra uso di un OSC, PM e PKAC. In conclusione, il presente lavoro discute i contributi di questa ricerca alla letteratura sulla MCC e alla pratica manageriale e ne presenta le limitazioni nonché le relative opportunità di ricerca futura.

1. Introduction

Many companies nowadays need to develop mass-customization capability (MCC), which is defined as an organization's ability to provide customized products and services that fulfil each customer's idiosyncratic needs without considerable trade-offs in cost, delivery, and quality (e.g., Pine, 1993; Liu et al., 2006; Squire et al., 2006; Sandrin et al., 2014; Suzic et al., 2018). One of the major developments in the practice of companies offering customized products over the last two decades is the heavy use of online sales configurators (Fogliatto et al., 2012; Blazek et al., 2016). Online sales configurators (OSCs) are software applications that enable customers to self-customize their product solutions online. Previous research describes OSCs as one of the fundamental tools characterizing mass customization and, not by chance, they are also called mass-customization toolkits (Franke et al., 2010).

While the mass customization literature presents a good deal of evidence that OSCs may improve customers' mass-customization experience and may help them choose the right customized product for themselves (e.g., Franke and Hader, 2014; Trentin et al., 2014; Walcher et al., 2016), empirical evidence about the impact of OSCs on MCC is very limited. Previous findings suggest the use of OSCs has a positive effect on MCC (e.g., Heiskala et al., 2007), but large-scale empirical studies focused on this impact are still missing. The purpose of this thesis is to contribute to filling this gap by investigating the effect of OSC use on MCC. In doing that, the present work takes into account two contextual factors that the existing literature suggests may influence this impact. These factors are product modularity (Hvam et al., 2004; Heiskala et al., 2007) and product knowledge absorption from customers (Felfernig, 2008; Zhang, 2014). Product modularity (PM) is defined as "a product design concept in which products of one product family are partitioned into highly independent (or loosely coupled) and preferably function-specific product modules with standardized interfaces and high combinability" (Suzic et al., 2018: 16), while product knowledge absorption from customers (PKAC) is defined as a company's ability to acquire product knowledge from its customers, and to assimilate and apply that knowledge (Cohen and Levinthal, 1990; Todorova and Durisin, 2007; Zahra and George, 2002; Zhang et al., 2015a).

Based on logical reasoning and previous research findings, this dissertation develops a conceptual argument for the hypothesis that OSC use, PM, and PKAC have a positive complementary effect on MCC by mutually reducing their implementation costs and by mutually reinforcing their benefits in terms of MCC. This hypothesis is subsequently tested using survey data from an international sample of manufacturing plants and three different approaches that have complementary pros and cons.

The rest of the thesis is organized in five sections. A review of the relevant literature and the development of the research hypothesis are presented in Sections 2 and 3, respectively. The methods used for testing the hypothesis are described in Section 4. Section 5 reports the results of the analyses. Finally, Section 6 discusses the results, indicates limitations of the present research, and provides suggestions for future research.

2. Literature review and research objective

2.1 Mass customization and mass-customization capability

The concept of mass customization appeared for the first time in 1987 in Stanley Davis's book *Future Perfect*. Davis (1987) stated that mass customization was a concept that was particularly fitted to new economic developments. Indeed, at the beginning of 1990s, mass customization entered the scene and took its place on the market as a valid and very often indispensably key strategy for the survival of many businesses. The seminal book by Pine (1993) further contributed to the dissemination of the mass customization paradigm by exploring the strategies, methods, and organizational transformations required for shifting to mass customization. The transition to mass customization is a concern for companies that historically came from both mass production and craft production companies (Forza and Salvador, 2006), as explained hereafter.

Offering customized products is by no means a new phenomenon. Artisan workshops have always designed, manufactured, and sold products according to their customers' specifications. Besides artisans, other businesses have also traditionally produced customized and complex products, for example, large mechanical workshops, construction companies, and shipyards. However, this kind of customized production had low repetitiveness of operations in the value chain, which implied low productivity, high production costs, and long delivery times (see "craft production" in Figure 2-1). An important attempt to alleviate the operational performance penalties that product customization generates was the "standardization movement" (see arrow "a" in Figure 2-1). This movement, born in the US at the beginning of the twentieth century, laid the foundations for mass production. A remarkable example of this shift towards mass production occurred when Henry Ford introduced this new production paradigm in his factory. In 1916, the mass production of the Ford Model T allowed Mr. Ford to sell an automobile for $360, when usually the automobile price was over $2,000 (Forza and Salvador, 2006). From that point, mass production became increasingly widespread, providing standardized products with low production costs. In that period, customers were prepared to sacrifice what they actually wanted in favor of more affordable products. However, in the mid-twentieth century, many mass markets reached saturation and the dominance of mass production started to fade (Koren, 2010). Therefore, companies were forced to create products that satisfy the specific needs of different market segments. The need for mass-production companies to increase product variety while preserving mass-production efficiency has pushed many mass producers to embrace mass customization (see arrow "b" in Figure 2-1).

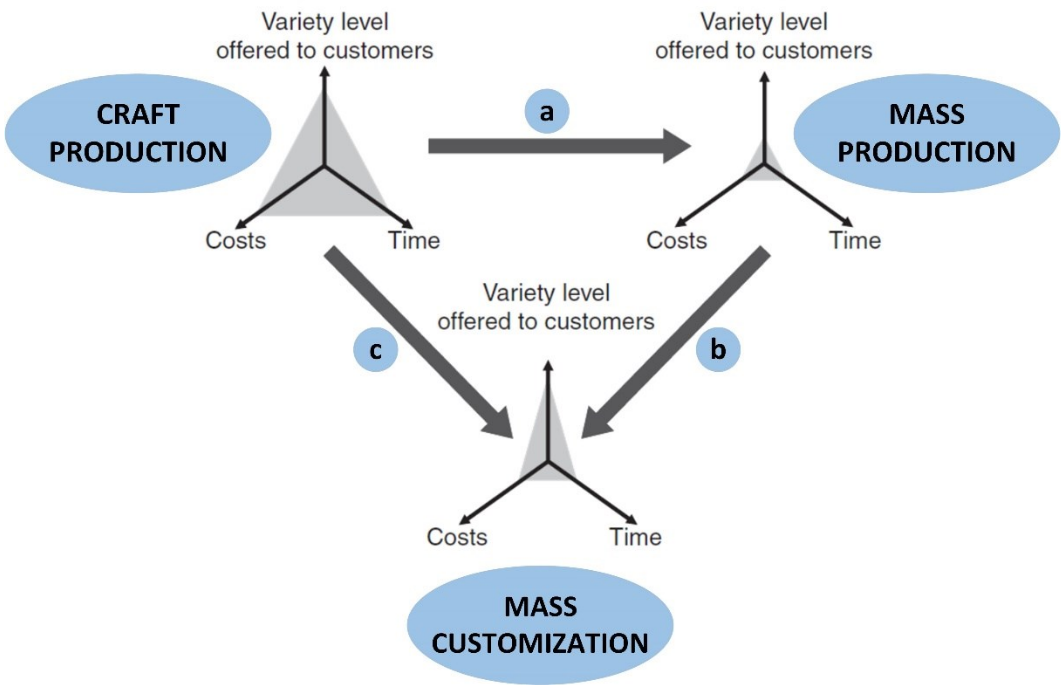


Figure 2-1: Different paths towards mass customization (adapted from Forza and Salvador, 2006)

It should be noted that mass production has never been extended to all types of companies. Many companies that offer a specific product tailored to their customers' needs (e.g., cranes, air conditioning systems for business applications, etc.) seldom reach high production volumes and, therefore, cannot qualify as mass producers. However, these craft-production companies are increasingly pushed by competition on the global market to lower their prices and speed up delivery lead times. In other words, they are forced to improve their operational performance without sacrificing their product variety and customization offerings, thus moving them toward mass customization as well (see arrow “c” in Figure 2-1).

The term mass-customization capability was introduced in the literature by Tu et al. (2001), who conceptualized this organizational capability as a competitive performance by defining it as the ability to produce differentiated products without sacrificing manufacturing costs and delivery lead-times. Notably, the conceptualization of organizational capabilities as competitive performance, or operational strengths, is typical of the operations management literature (Peng et al., 2008). However, another view of organizational capabilities, which is typical of the strategic-management literature, conceptualizes them as combinations of organizational routines, which are repetitive patterns of interdependent organizational actions (Parmigiani and Howard-Grenville, 2011).

More in line with the latter view of capabilities, Zipkin (2001) spoke of three MCCs: elicitation, process flexibility, and logistics. These capabilities can be seen as means a company should use to achieve the MCC defined by Tu et al. (2001). Elicitation comprises mechanisms for interacting with the customer and obtaining specific information about what he/she wants. Process flexibility requires a production system that fabricates the product according to the customer information, and logistics permits to maintain the identity of each product and to deliver the right one to the right customer (Zipkin, 2001).

Zipkin's (2001) three MCCs are echoed by Salvador et al.’s (2008, 2009) organizational capabilities of solution space development, robust process design, and choice navigation. Solution space development is the ability to identify the product attributes along which customer needs diverge. Robust process design is the ability to reuse or recombine existing organizational and value-chain resources to fulfill a stream of differentiated customer needs. Finally, choice navigation is the ability to support customers in identifying their own solutions while minimizing complexity and the burden of choice (Salvador et al., 2009). Again, these three capabilities can be seen as antecedents of the MCC defined by Tu et al. (2001).

Even though both Zipkin's (2001) and Salvador et al.'s (2008, 2009) works demonstrate that the "performance" view of MCC is not universally shared, it must be acknowledged that it is by far the most commonly adopted in literature. In accord with this view, the present thesis defines MCC as *an organization's ability to provide customized products and services that fulfil each customer's idiosyncratic needs without considerable trade-offs in cost, delivery, and quality performance* (e.g., Pine, 1993; Liu et al., 2006; Squire et al., 2006; Sandrin et al., 2014; Suzic et al., 2018).

2.2 Online sales configurators

More and more companies that offer product customization use online sales configurators (OSCs) to offer their products on the Internet (Fogliatto et al., 2012; Grosso et al., 2017). This trend is witnessed by the steady increase in the number of OSCs on the web (Walcher and Piller, 2012; Abbasi et al., 2013; Blazek et al., 2016). It is supported by the developments in information and communication technologies and is also sustained by the growing necessity for companies to have an active Internet presence in order to be competitive on the global market. Online sales configurators *are web-based software applications that guide a potential customer in completely and correctly specifying an admissible product solution within a company's product offering (also known as product space or solution space)* (e.g., Heiskala et al., 2007; Forza and Salvador, 2008; Sandrin et al., 2017).

Offline sales configurators are usually designed to be used by salespeople working with customers, but only rarely by customers alone. On the contrary, OSCs are sometimes used by salespeople, but, in most cases, they are designed to be used by customers alone. An online (as well as offline) sales configurator can be implemented as a stand-alone software application, or can be integrated with what is known as a technical configurator to constitute a broader product configuration system, known as a product configurator (Hvam et al., 2006; Forza and Salvador, 2008; Tiihonen et al., 2013). If a sales configurator is integrated with a technical configurator, the resulting product configurator will automatically generate not only complete and valid sales specifications (through the sales configurator), but also the product data (e.g., bills of materials) and manufacturing data (e.g., production routings) needed to translate those specifications into a real product (through the technical configurator).

The fundamental function of an OSC is to enable a potential customer to explore a company's product space and to completely and correctly define a desired product solution within that space (Franke and Piller, 2003; Heiskala et al., 2007; Forza and Salvador, 2008; Sandrin et al., 2017). The product space, also known as the solution space (von Hippel, 1998; Salvador et al., 2009), represents "the pre-existing capability and degrees of freedom built into a given manufacturer's production system" (von Hippel, 2001: 251). Mass customization allows customers to express and search for solutions for their needs by defining, configuring, matching, or modifying an individual solution within a given product space (Tseng and Du, 1998; von Hippel, 1998; Franke and Piller, 2003). Stated otherwise, in a mass-customization context, customers are included in the process of value creation (Piller, 2004; da Silveira, 2011) by participating in defining the product that satisfies their needs within the limitations set by the company (Forza and Salvador, 2002a; MacCarthy et al., 2003; Salvador et al., 2009). In summary, OSCs support the order specification process, also known as the commercial (or sales) configuration process (Forza and Salvador, 2006).

During this process, a company interacts with a potential customer to obtain information regarding the specifications of his/her desired product and to communicate what the enterprise can offer, how these offerings respond to specific customer needs, and under which conditions (e.g., price and delivery lead-time conditions) the transaction is possible (Forza and Salvador, 2006). This process includes all the activities carried out to identify the complete and congruent commercial description of the product (i.e., commercial [or sales] [product] configuration) that best fits the customer's requirements. When the customer and the company agree on the solution that will be provided, this process ends with the acquisition of the customer order. The order specification process is of paramount importance for two reasons. First, as mentioned above, this process includes the communication of its product offer characteristics by the company to the customer. A well communicated product offer raises the chances that the customer will be able to configure the product solution that best satisfies his/her needs and will decide to purchase the configured product. Second, the order specification process produces a description of the ordered configuration. Based on this description, the customer sets his/her expectations regarding the functions and performance of the product. Accurate communication of the product characteristics during the sales specification process leads to higher customer satisfaction with the product during the product's lifetime.

An OSC communicates with customers through a sequence of questions that is usually called a "commercial dialogue." The commercial dialogue that a customer sees while interacting with an OSC is based on a pre-designed repository of knowledge called a "commercial model." The commercial model is "a formal representation of the product space and of the procedures according to which a commercial configuration can be defined within such space." (Forza and Salvador, 2006: 53). Sometimes, however, the terms “commercial dialogue” and “commercial model” are used as synonyms. The set of activities through which the necessary knowledge for commercial product configuration is gathered and processed into a commercial model is called the commercial modeling process (Forza and Salvador, 2006).

The commercial dialogue is often supported by multimedia features such as images or 3D graphics of the entire product and/or of the specific options from which a customer can choose. By responding to each question, that is, by selecting one of the choice options associated with that question, the customer progressively defines all of the product’s characteristics. Often an OSC also provides explanations for why a certain choice could be good for the customer; that is, it explains which needs are satisfied by a certain option. Ideally, the commercial dialogue should be able to communicate the value of the different alternatives (Forza and Salvador, 2006) so customers can understand if the solution space presented in the OSC offers options that satisfy their needs and, if so, which options do that better. In this way, an OSC can help improve the fit between a customer’s idiosyncratic needs and the product solution the customer configures (Hvam et al., 2006; Forza and Salvador, 2008). Additionally, an OSC can dynamically provide the prices associated with the selected options (Forza and Salvador, 2006). This allows the customer to understand how certain options affect the price of the product solution he/she is configuring and if they are in line with his/her budget constraints (Forza and Salvador, 2006).

Ideally, the structure of an OSC commercial dialogue should also enable a spontaneous interaction process with customers; that is, customers should be allowed to search the variety of options offered by the company in their most natural way (Forza and Salvador, 2006). For example, the sequence of questions in a commercial dialogue may follow, as closely as possible, the order the customer typically uses when describing or specifying the product. A sequence designed in this way makes the sales configuration process more comprehensible for customers and, therefore, more comfortable to use.

However, the design of the sequence of the questions might not be totally free from constraints. For example, the presence of constraints between different product attributes could entail that some questions must be asked before others, as the set of possible choices for a specific attribute depends on previous choices made for other attributes. The presence of constraints in the commercial dialogue can even imply that no choice is allowed for a certain attribute (and therefore the attribute disappears from the commercial dialogue). For example, during a bike configuration, the choice of “light city bike” could reduce the available options for the attribute “frame material” to only “aluminum” and “carbon,” excluding other choices, such as “stainless steel,” from the available options. Additionally, the same choice of “light city bike” could completely eliminate the possibility to have an “advanced gear shift,” which would substantially increase the weight of the bike.

In addition, the OSC commercial model should describe the product space in the most suitable way for the targeted customers. The most suitable way to describe a product to the customer depends on many factors, including the product’s complexity, its importance for the customer, and the customer’s willingness to learn about the product (Forza and Salvador, 2006). These factors influence the way the customer wishes to express his or her needs. For example, a potential buyer of a personal computer (PC) could ask for a computer that is “good enough for gaming but not too costly.” This type of buyer (an amateur gamer) is interested only in certain performance dimensions, not in the exact components built into the computer. Another type of potential buyer, a more skilled gamer, might prefer to express his/her preferences in terms of functionality rather than in terms of performance dimensions. This means that he/she would ask for a system that has a certain processing capacity or storage capacity. Finally, a professional gamer with high knowledge about the product would be likely to choose each and every component (e.g., a certain processor from a certain supplier, a certain hard disk from a certain supplier, etc.) and would probably ask for some special solutions at the component level (e.g., an upgraded cooling system). From the previous example, it can be seen how the description of the product can vary in terms of its level of abstraction, from a description based on performance dimensions to a description based on functionalities to a description based on physical components (Figure 2-2). Notably, all three variations are based on attributes, but the attributes differ in their nature: performance dimensions, functionalities, or physical components. Frequently, an OSC commercial dialogue is able to describe the product in several ways, at different levels of abstraction, in order to communicate effectively with potential buyers with different individual characteristics (Forza and Salvador, 2006; Trentin et al., 2013). For example, the OSC commercial dialogue for a personal computer could start with the question: “Would you like to: (1) choose among predefined configurations, (2) choose by functions required, or (3) choose each component specifically?” Depending on the answer to this question, a different sequence of questions would be asked of the customer in order to provide him/her with better guidance though the sales configuration process (Figure 2-2).

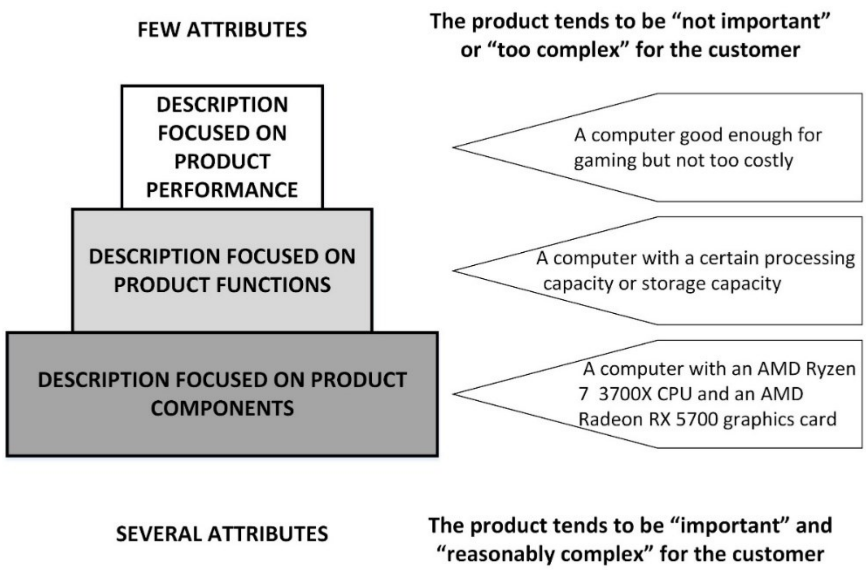


Figure 2-2: Product descriptions with different degrees of abstraction (adapted from Forza and Salvador, 2006)

2.3 Online sales configurators and mass-customization capability

The mass-customization literature recognizes OSCs as an important tool for mass customization (Franke et al., 2010). Several benefits that a firm pursuing a mass-customization strategy can derive from the use of an OSC have been discussed or suggested in prior studies.

A first important benefit that can be achieved through an OSC that exhibits certain characteristics is the reduction of the cognitive complexity perceived by the customer during the sales configuration process. This reduction is important in order to avoid the “product variety paradox” that occurs “when offering more product variety and customization in an attempt to increase sales paradoxically results in a loss of sales” (Trentin et al., 2013: 436). Companies that provide customized products could easily overwhelm their customers with the numerous options offered. In that case, customers face cognitive complexity, which means that high effort is required of customers to understand what the company offers and to make choices that better satisfy their requirements. One of the fundamental ways of reducing cognitive complexity is to improve the customer’s understanding of the company’s offer (Forza end Salvador, 2006). Online sales configurators with certain characteristics help the customer understand and learn about the company’s offer, thus increasing the customer-perceived benefits of a mass-customized product (Sandrin et al., 2017). These configurators enable customers to engage in a trial-and-error process in which they can change, from time to time, the selected options. If this exploration is accompanied by the possibility of easily comparing the different product configurations, the customer will almost effortlessly learn about the company’s product offering and how his/her requirements can be satisfied by different options. This learning process increases the customer-perceived fit of the configured product with his/her own preferences (Sandrin et al., 2017). In this way, mass customizers can increase sales (Huang et al., 2019). Higher sales translate into higher production and sourcing volumes, which in turn lead to scale economies in production and purchasing and, thus, reduce product unit cost. This reduction makes customized products more affordable, thus increasing MCC.

In addition, the use of an OSC increases the accuracy and speed of the sales configuration process (Barker and O'Connor, 1989; Forza and Salvador, 2002a, 2002b; Hvam et al., 2004; Heiskala et al., 2007). This is because the OSC immediately and automatically checks for the completeness and validity of the created product specifications. As a result, the OSC provides the company with commercial product specifications that are free of errors (Tiihonen et al., 2013). Therefore, the company does not need additional time for feasibility checking and error correction, thus lowering the cost of the sales configuration process while assuring quality and, consequently, improving MCC. Further, by immediately and automatically checking the completeness and validity of product specifications, an OSC cuts the company's lead times for generating quotes for customer requests (Bramham and MacCarthy, 2004; Hvam et al., 2006; Hvam et al., 2008). Reducing these lead times increases the probability of winning orders and, accordingly, increases sales, which again leads to higher MCC, as explained above.

Further, OSCs can help reduce the number of offers and orders for ad-hoc solutions (Forza and Salvador, 2002a; Heiskala et al., 2007; Trentin et al., 2012). The automated generation of price and/or cost information by an OSC may be used to drive the customer towards a predefined solution that costs less than an ad hoc solution but equally fulfills his/her specific needs (Trentin et al., 2012). Fewer ad hoc solutions means higher quality, lower costs, and shorter delivery lead times, thus improving MCC.

Another advantage of OSCs lies in their ability to enable potential customers to explore a company's offerings autonomously on the Internet. Thus, an OSC can help expand the base of potential customers, thereby achieving wide customer coverage at a low cost. In brief, an OSC can help companies reach and expand into new international markets. In addition, OSCs can have an e-commerce function, allowing customers to place orders online, potentially without any direct contact with the company's sales personnel (Walcher and Piller, 2012). In the end, this is likely to increase sales (Auger and Gallaugher, 1997). Higher sales volumes translate into higher production volumes, which imply lower unit costs and, ultimately, higher MCC.

2.4 Factors affecting the impact of online sales configurators on mass-customization capability

In summary, there are several mechanisms through which the use of OSCs can improve MCC. The working of these mechanisms must not be taken for granted, however. For example, the potential benefits derived from the reduction of customer requests and orders for ad-hoc solutions actually materialize if and only if the product space offered through the OSC, and the way this solution space is communicated to customers, are appropriate. Otherwise, customers will be forced to ask for ad-hoc solutions outside the solution space or will even abandon the configuration process, *tout court*. As Blazek and Pilsl (2017) pointed out, a considerable number of OSCs disappear from the Internet every year. In many cases, the OSCs disappear because they did not properly address configurator implementation and exploitation challenges (Kristjansdottir et al., 2018) and, thus, failed to deliver the promised benefits in terms of MCC.

Previous research suggests that the effects of OSCs on MCC could depend on the adoption of other organizational practices that complement OSC use. For example, Hvam et al. (2013) reported the case of a successful company where the use of product configuration systems is part of an overall business strategy that also includes a modularized product assortment and a market focus. This finding echoes, or is echoed by, other indications, scattered in the mass-customization literature, that product modularity and the absorption of product knowledge from customers can enhance the impact of OSCs on MCC.

2.4.1 Product modularity

Product modularity (PM) is defined in this thesis as "*a product design concept in which products of one product family are partitioned into highly independent (or loosely coupled) and preferably function-specific product modules with standardized interfaces and high combinability*" (Suzic et al., 2018: 16, based on Sanchez and Mahoney, 1996; Baldwin and Clark, 1997; Dyray et al., 2000; Schilling, 2000; Langlois, 2002; Salvador et al., 2002, Mikkola and Skjøtt-Larsen, 2004; Salvador, 2007). Ideally, a product is modular if its functional requirements map one-to-one to its physical components (i.e., each component implements one and only one function and each function is implemented by one and only one component) and the component interfaces are decoupled (i.e., a component will not have to change when the surrounding parts are modified) (Ulrich, 1995).

Product modularity has been considered a means to increase part commonality across different product variants within a product family, that is, to allow the same modules to be used in multiple (possibly all) product variants (Evans, 1963; Salvador et al., 2002). As a result, PM reduces the number of different parts needed for the manufacturing of customized products (Tu et al., 2004). This reduction in the number of parts enables a company to increase part/module volumes and, consequently, to decrease unit costs (Duray et al., 2000). Further, part commonality also reduces part/module inventory-holding costs while guaranteeing the same level of availability of parts and modules for the final assembly. Additionally, part commonality improves product quality (Duray et al., 2000; Kumar, 2004; Shamsuzzoha et al., 2010) because even a product variant created for the first time is composed of parts and modules that have already been used in previously sold products, which means that possible quality problems affecting these modules have already been detected and solved, at least to some extent. In summary, through part commonality, PM reduces the costs and preserves the quality of customized products, thereby increasing MCC.

Furthermore, PM provides a favorable environment for customers to co-create products (Peng et al., 2011). First, decoupled interfaces enable the creation of different product variants by simply exchanging one module with another. Second, one-to-one mapping of functional requirements onto physical components simplifies the translation of customer requirements into sales specifications (Tiihonen et al., 1996: 107) and facilitates communication of a company's product offer to its customers (Hvam et al., 2011). Indeed, good long-term results from the use of a product configurator can only be expected when the product has an easily configurable design (Tiihonen and Soininen, 1997) and an easily configurable product design often means using a product architecture based on the notion of PM (Hvam et al., 2004; Heiskala et al. 2007). In brief, prior research suggests that PM makes the sales configuration process more efficient and effective and facilitates the design and maintenance of the OSC.

2.4.2 Product knowledge absorption from customers

Product knowledge absorption from customers (PKAC) is defined in this thesis as *an organization's ability to acquire product knowledge from customers, assimilate that knowledge, and apply that knowledge* (based on Cohen and Levinthal, 1990; Todorova and Durisin, 2007; Zahra and George, 2002; Zhang et al., 2015a). A company can acquire knowledge from customers through different routines and mechanisms, such as real-time information sharing, special meetings or surveys, and interactions (Hult et al., 2004; Jansen et al., 2005). Knowledge assimilation, defined as the ability to analyze, interpret, and understand external information (Todorova and Durisin, 2007; Zahra and George, 2002), can be accomplished through various practices, such as group learning, collaborative problem solving, and knowledge sharing routines (Hult et al., 2004; Jansen et al., 2005; Tu et al., 2006; Zahra and George, 2002). Finally, knowledge application refers to the exploitation of knowledge that allows companies to refine, extend, and leverage existing competencies or to create new ones by incorporating acquired and transformed knowledge into their operations (Zahra and George, 2002). Exploitation of customer knowledge in new product development or in process improvement are typical examples of knowledge application.

Customers can provide valuable external product knowledge, as they have product-related information about the application, function, features, use, and support requirements of a product. Absorption of this knowledge from customers (i.e., PKAC) allows the development of a solution space that fits better the customers' needs (Kristal et al., 2010; Zhang et al., 2015a). Consequently, customers will be more likely to find the right product for them inside the offered product space (Salvador et al., 2009; Trentin et al., 2012; Zhang et al., 2015a), which increases the chances that they will buy the product. In turn, more sales imply higher production and sourcing volumes and, consequently, lower product unit costs and, ultimately, higher MCC. Additionally, if customers can find what they want within the company's product space, then these customers will not ask for ad-hoc solutions. Consequently, the number of quotations and orders for ad-hoc solutions will be lower, which also leads to higher MCC.

Product knowledge absorption from customers plays an important role in the design of an OSC. In general, designing a product configurator necessitates an intensive application of knowledge elicited from different domains, both internal and external to the company (Felfernig, 2008; Zhang, 2014). In particular, the acquisition of knowledge about customers' needs was recognized by Kristjansdottir et al. (2018) as one of the main challenges in configurator implementation. To acquire knowledge about customer needs, Haug et al. (2019) recommends involving future users in configurator design. Future users possess a specific kind of external product knowledge. Formalization of this knowledge into the commercial-configuration model raises the configurator user acceptance and reduces the risk of failure. In summary, prior research findings suggest that PKAC is another contextual factor that influences the impact of using an OSC on MCC.

2.5 Research objective

While several benefits that a firm pursuing a mass-customization strategy can derive from the use of an OSC have been discussed or suggested in prior studies, the existing literature still lacks a large-scale empirical study that examines the impact of OSC use on MCC. This thesis aims to contribute to filling this gap using survey data from a sample of mid- to large-sized manufacturing plants in 3 industries and 15 countries around the globe.

As explained in greater detail in the previous section, some of the studies that have investigated configurator implementation and utilization challenges as well as possible reasons for configurator projects failures (e.g., Kristiandottir et al., 2018; Haug et al., 2019) implicitly suggested that product configurators (including OSCs) need to be implemented along with PM and PKAC to overcome such challenges and to properly address target customers. These indications are supported by the results of a number of case studies (e.g., Tiihonen et al., 1996; Hvam et al., 2011; 2013). Therefore, the investigation of the impact of OSC use on MCC must not neglect the roles of PM and PKAC. Accordingly, the objective of the present research is specified as follows: *to conceptually and empirically investigate how the combination of OSC use, PM, and PKAC impact an organization's MCC.*

To address this research objective, the theory of complementarities will be used, and Ennen and Richter's (2010: 207) definition of complementarities as "the beneficial interplay of the elements of a system where the presence of one element increases the value of others" will be adopted. The interplay of OSC use, PM, and PKAC will be conceptually examined in the following chapter.

3. Hypothesis development: Complementarities between online sales configurator use, product modularity, and product knowledge absorption from customers

A conceptual examination of the interrelationships between OSC use, PM, and PKAC shows that these three practices reciprocally reduce the costs of their implementation and mutually increase their benefits in terms of mass-customization capability. The following section describes the mechanisms that underlie reciprocal cost reduction, while Section 3.2 describes the mechanisms behind mutual benefit amplification.

3.1 Mutual reduction of implementation costs

Based on the mass customization literature, it can be argued that OSC, PM, and PKAC mutually reduce their implementation costs. Considering that cost reduction plays an important role in developing MCC, it can be concluded that this mutual reduction of implementation costs has a positive effect on MCC. The mechanisms underlying this mutual cost reduction are summarized in Table 3-1.

Table 3-1: Mutual implementation-cost reduction between OSCs use, PM, and PKAC

	Implementation costs of OSC…	**Implementation costs of PM…**	**Implementation costs of PKAC…**
…are reduced by OSC		OSC development requires identifying a product's functional elements and their mapping to the product's physical components, which is also required by PM	OSC allows for retrieving information about completed product configurations that customers have not converted into purchase orders. In turn, the analysis of such configurations permits the acquisition of customer information, such as systematic preferences for one product solution over another one
…are reduced by PM	PM reduces the number of constraints that must be inserted in an OSC commercial model		PM leads to modular product knowledge, i.e., highly decomposable knowledge, which facilitates the design of systems and routines to collect and store product-related information from customers
…are reduced by PKAC	PKAC provides product-related information, such as customers' preferences concerning how a product should be described in the OSC commercial dialogue, which reduces the risk of trial-and-error loops	PKAC provides product-related information that is crucial to identifying the functions that fulfill customers' demands and their corresponding technical solutions (modules)	

3.1.1 The implementation costs of OSC are reduced by PM and PKAC

The effort required for OSC development is reduced by PM (Tiihonen et al., 1996; Peng et al., 2011). There are two essential aspects of PM: one-to-one correspondence between functionalities and modules, which implies that one product function is assigned to a single module that implements that function; and the use of standard interfaces between families of modules (Ulrich, 1995; Sanchez, 1999; Salvador et al., 2002). These two aspects enable the creation of different product variants, with different functionalities, by simply exchanging one module with another. Stated otherwise, in a perfectly modular product architecture, modules can be mixed and matched freely. If this is the case, it is not necessary to include constraints in the OSC commercial-dialogue model. More generally, the number of constraints that must be included in an OSC model drops as the degree of PM increases. This means that setting up an OSC becomes simpler and requires fewer working hours, thus leading to lower costs, even if the number of possible product configurations within the company's product space is very high. Additionally, module interchangeability simplifies product price recalculation when a customer changes one of his or her choices during the sales configuration process. This is because the price change is limited to the specific module that implements the specific function for which the customer is changing his or her choice.

The effort required for OSC development is also reduced by PKAC. Acquiring information about customers' needs is one of the main challenges in the implementation process of a product configurator (Kristjansdottir et al., 2018). Overcoming this challenge requires eliciting adequate information from customers and applying it in the implementation process. Being able to do that leads to fewer trial-and-error loops before managing to develop a commercial model suited to the target customers (Hvam et al., 2008). Consequently, the time needed for OSC development is shorter and, therefore, the costs are lower. Moreover, the risks of delays or even implementation failure are reduced.

3.1.2 The implementation costs of PM are reduced by OSC and PKAC

The effort required for modularizing a product is reduced by the presence of an OSC. To be able to describe the offered product functionalities and their advantages, an OSC and the associated commercial model need to be developed based on identifying the product's functional elements and their correspondence with the product's physical components (Tiihonen and Soininen, 1997; Forza and Salvador, 2006). This activity, in addition to the definition of decoupled interfaces among product components, is also required by the development of a modular product. Therefore, in the presence of an OSC, this activity has already been done and, hence, PM implementation costs are lower.

The effort required for modularizing a product is also reduced by PKAC. To be able to modularize a product in a way that meets customers' preferences, a company needs to know what customers want from a product (Ericsson and Erixon, 1996). In Ericsson and Erixon's (1996) "Modular Function Deployment" method, the first step to finding the optimal modular product design is to acquire product-related information from customers and to use it to design product requirements. Subsequently, in step two, these product requirements are key inputs to the so-called "functional decomposition," that is, to the identification of the functions that fulfill customers' demands and their corresponding technical solutions (modules). This means that, without PKAC, there is a higher risk of developing a product family whose modular architecture is not well fitted to the heterogeneity of target customers' needs. Instead, as PKAC increases, the risk of trial-and-error loops before managing to develop a modular product family that fits those needs is lower and, therefore, PM implementation costs decrease.

3.1.3 The implementation costs of PKAC are reduced by OSC and PM

The effort required for developing PKAC is reduced by an OSC. The log files generated by the browsing behavior of people using OSCs represent a valuable source of product-related information from customers. For example, based on an analysis of the product configurations that have been evaluated but not ordered, a company could learn much about its customers' preferences and eliminate options that are rarely explored (Salvador et al., 2009). Therefore, an OSC cuts the cost of setting up a system to gather product-related information. Furthermore, the cost of developing a system to analyze this information is reduced as well, because this information is structured according to the logic embedded in the OSC commercial model. In summary, an OSC reduces the costs of developing PKAC with regard to both the collection of product-related information from customers and the subsequent analysis of that information.

The effort required for developing PKAC is also reduced by PM. A modular product architecture leads to modular product knowledge, which tends to be highly decomposable with pieces that are loosely coupled (Yayavaram and Ahuja, 2008). In particular, product-related information can be decomposed and stored in small pieces according to the product's functionalities and sub-functionalities, which in turn are clearly mapped to physical components. Consequently, the design of systems and routines to collect and store this information tends to be easier and less expensive in comparison with the case of an equivalent product characterized by an integral architecture. Besides collection and storage, the application of the information absorbed from customers is also facilitated by PM. The decoupling of the interfaces between modules and the consequent possibility of using the same module across many different product solutions implies that any module improvement inspired by, for example, an analysis of product configurations that have been evaluated but not ordered, can be more easily applied to a larger part of the company's solution product (Wang et al., 2014). In other words, knowledge application is simpler and less expensive.

3.2 Mutual amplification of benefits in terms of mass-customization capability

Logical reasoning and, in a few cases, prior research findings indicate that the beneficial effects of OSC use, PM, and PKAC on MCC are mutually amplified. The mechanisms underlying this mutual amplification are summarized in Table 3-2.

Table 3-2: Mutual amplification of the benefits, in terms of MCC, among OSC, PM, and PKAC

	Benefits provided by OSC…	Benefits provided by PM…	Benefits provided by PKAC…
…are amplified by OSC		OSC reduces the number of orders for ad-hoc engineered product solutions. This permits a fuller realization of the potential benefits of PM in terms of lower costs, faster deliveries, and higher quality due to component commonality	OSC automates the commercial dialogue that PKAC makes more user-friendly and, therefore, faster. As a result of automation, the sales configuration process is sped up further, with stronger positive effects on sales volumes and, ultimately, on MCC
…are amplified by PM	PM makes various product functionalities independent of one another, thus eliminating constraints among the related choices in the OSC commercial dialogue. Thus, it becomes easier for a customer to change his/her earlier choices and to compare the obtained results. This improves the customer's learning process and, hence, increases perceived preference fit. In turn, this amplifies the positive effect that the use of an OSC has on MCC as a result of the increase in sales and production volumes and the consequent reduction of unit costs		PM permits module improvements driven by PKAC to affect a larger part of the company's product space, thus amplifying the positive effect of PKAC on MCC

…are amplified by PKAC	PKAC makes it easier to tailor the OSC commercial dialogue to different target customers, which makes the OSC more user friendly. This improves a customer's learning process and, hence, increases perceived preference fit. As a result, the increase in sales and production volumes due to the use of an OSC is amplified, which reinforces the positive effect of OSC use on MCC through the reduction of unit costs	PKAC reduces the number of orders for ad-hoc engineered product solutions, thus permitting fuller realization of the potential benefits of PM in terms of MCC that derive from component commonality	

3.2.1 The MCC benefits provided by OSC are amplified by PM and PKAC

The great advantage of using an OSC lies in its ability to substitute for salespeople and to allow customers to autonomously explore a company's product space. This expands the company's base of potential customers, with positive effects on the company's sales (Auger and Gallaugher, 1997). Higher sales volumes translate into higher production volumes, which imply lower unit costs and, ultimately, higher MCC.

However, with an integral product architecture, characterized by combinability constraints among product components, it could happen that, during the exploration of the company's product space, a customer who wishes to change just one of the product options he/she has previously selected is actually forced to change many other choices. This lengthens the sales configuration process and can make it less understandable for the customer, which may even lead the customer to quit the process, with the consequent loss of a potential sale. Conversely, with a modular product architecture, a customer can change his/her choice about a certain product functionality without having to change other options selected during the OSC commercial dialogue. In other words, a modular product architecture makes it easier for the customer to change his/her earlier choices and compare the obtained results, which improves the customer learning process (Sandrin et al., 2017). When customer learning is improved, customers are more likely to succeed in creating the product configuration that best fits their needs, as repeatedly argued in previous studies on mass customization and sales configurators (e.g., Von Hippel, 2001; Randall et al., 2005; Salvador and Forza, 2007; Franke and Hader, 2014; Sandrin et al., 2017). In turn, higher perceived preference fit increases the probability that the customer will buy the product he/she has configured. In summary, by making the customer's exploration of the company's product space more flexible, PM enhances the positive effect that the use of an OSC has on MCC as a consequence of the increase in sales and production volumes and the consequent reduction of unit costs.

Likewise, the positive impact of OSC use on MCC is reinforced by PKAC. The practice of PKAC makes it easier to tailor the OSC commercial dialogue to the different needs and abilities of different target customers. Potential customers vary in terms of involvement with, and prior knowledge about the product, in terms of cognitive abilities, and, therefore, the way a company's product space is described by the OSC should not follow a "one-size-fits-all" approach (Trentin et al., 2013). By making the OSC more user-friendly, PKAC improves the customer's learning process and, therefore, increases customers' perceived preference fit (Sandrin et al., 2017). In summary, PKAC raises the chances that the customer will configure the right product and will therefore buy it, thus enhancing the impact of OSC use on MCC.

3.2.2 The MCC benefits provided by PM are amplified by OSC and PKAC

Product modularity increases component commonality within a product family (Ulrich, 1995). As a result, the number of different parts needed for a set of product variants is reduced (Tu et al., 2004). Fewer parts means higher production volumes for each part and, hence, lower unit costs (Duray et al., 2000). Further, part commonality also reduces inventory-holding costs while guaranteeing the same service level (Baker, 1985; Hillier, 1999). Finally, part commonality improves product quality (Duray et al., 2000; Kumar, 2004; Shamsuzzoha et al., 2010). In summary, by increasing part commonality, PM reduces the cost and preserves the quality of customized products, thus increasing MCC.

However, to fully realize the potential benefits of PM in terms of lower costs and higher quality, the number of orders for ad-hoc engineered solutions that fall outside the predefined modular solution space should ideally be zeroed. The use of an OSC reduces this number (Forza and Salvador, 2002a; Heiskala et al., 2007; Trentin et al., 2012). For example, the automated generation of price information by the OSC may be used to drive the customer toward a predefined solution that costs less than an ad-hoc solution but equally fulfills his/her specific needs (Trentin et al., 2012).

Like the use of an OSC, PKAC also reduces the number of orders for ad-hoc solutions. The absorption of knowledge from target customers about desirable product features and functions allows the development of a product space that better fits customers' needs (Kristal et al., 2010; Zhang et al., 2015a). This increases the likelihood that customers will find the right product for themselves within the predefined product space (Salvador et al., 2009; Trentin et al., 2012; Zhang et al., 2015a). Consequently, the number of orders for ad-hoc solutions will be lower, which permits a fuller realization of the potential benefits of PM in terms of MCC.

3.2.3 The MCC benefits provided by PKAC are amplified by OSC and PM

As mentioned in Section 3.2.1, PKAC makes it easier to create commercial presentations of a company's product space that are tailored to the different needs and abilities of different target customers. This facilitates customer searches for suitable solutions within the company's product space, with a twofold effect. First, the need for clarification is reduced, which in turn shortens the search time (i.e., the sales configuration process is accelerated). Second, customer perceived preference fit is increased (Sandrin et al., 2017). Both effects translate into higher sales and production volumes, which in turn increase MCC.

The use of an OSC reinforces this positive effect of PKAC by further accelerating the sales configuration process. This is because an OSC immediately and automatically checks the completeness and validity of product specifications, thus providing the company with commercial product specifications that are free of errors (Tiihonen et al., 2013). As a result, the company does not need additional time for feasibility checking and error correction. This, for example, cuts the lead times for generating quotations for customers' requests (MacCarthy et al., 2003; Hvam et al., 2006; Hvam et al., 2008) whenever the order acquisition process includes quotation activities.

The practice of PKAC also improves MCC by allowing a company to provide its customers with a product space that is constantly aligned with their evolving needs (Kristal et al., 2010; Zhang et al., 2015a). This positive effect is amplified by PM. This is because, as explained in Section 3.1.3, PM facilitates the application of product-related information gathered from customers, thereby accelerating the adaptation of the company's product space. This gives the company a competitive advantage on the market, with positive effects on sales volumes and, ultimately, on MCC.

As a whole, the above discussion of the interrelationships between OSC, PM, and PKAC implies that each of these three practices has a stronger positive impact on MCC in a context where the other two practices have high values. Therefore, the following hypothesis is proposed:

H1: OSC use, PM, and PKAC have a positive complementary effect on MCC.

4. Methods

4.1 Testing for complementarities

This section formally introduces the notion of complementarity between elements of a system. In addition, three different approaches to testing for complementarities are described. Finally, the rationale underlying the combination of these approaches is discussed.

4.1.1 The notion of complementarity

Complementarity is an important concept in many disciplines, where it is used with varying meanings (Ennen and Richter, 2010). The present work focuses on the complementarity concept developed in the economics, organizational, and strategic literature. The concept of "complementarities" was originally introduced in economics by Edgeworth (1881), who defined two activities as complementary if doing more of one of them increases the returns from doing more of the other. An important contribution to the complementarity concept in the same field was made by Milgrom and Roberts (1990, 1994, 1995). By building on the work of Topkis (1978, 1987), they used the mathematical concept of supermodularity on lattices as an approach for formally modeling complementarities (Ennen and Richter, 2010), as explained later in the text. Complementarities occur when the marginal returns to one variable increase with the level of another variable and, because of such synergistic effects, bundling the two variables together in a production system results in an economic outcome that is greater than the sum of the contributions of the same two variables taken individually (e.g., Ennen and Richter, 2010; Milgrom and Roberts, 1995; Tanriverdi and Venkatraman, 2005). Using Ennen and Richter's (2010: 207) words, complementarities are defined in the present thesis as “the beneficial interplay of the elements of a system where the presence of one element increases the value of others.” This definition contains Edgeworth’s (1881) notion of complementary activities, which is at the basis of the seminal contribution made by Milgrom and Roberts (1990) in the economics literature. This definition, however, is more general, as it also captures complementarities among elements other than activities, such as “complementarities among different types of knowledge, skills, and capabilities on the individual level” (Ennen and Richter, 2010: 215) or complementarities “between organization-level characteristics and phenomena outside the organizations concerned” (Ennen and Richter, 2010: 214). The idea of complementarity has also been referred to in literature as interconnectedness, synergy, integration, fit or systems effects, as observed by Milgrom and Roberts (1995), Moorman and Slotegraaf (1999), and Ennen and Richter (2010). Essentially, this idea concerns how one element of a system influences another and how their relationship affects some performance variable (Wiengarten et al., 2013).

The analysis of complementarity developed by Milgrom, Roberts and others is based on the study of supermodular functions on lattices (cf. Milgrom and Roberts, 1990; 1995). A lattice is a partially ordered set X with the property that, for any x and y in X, X also contains a smallest member under the order that is larger than both x and y ($x \vee y$, read “x join y”) and a largest member that is smaller than both x and y ($x \wedge y$, read “x meet y”). For example, the set of real numbers, $\mathbb{R}$, with the usual order, is a lattice, and any subset of $\mathbb{R}$ is also a lattice. In brief, a set X is a lattice if it is closed under the meet (i.e., intersection) and join (i.e., union) operations:

$$\forall x, y \in X, x \wedge y \in X \text{ and } x \vee y \in X.$$

For the Euclidean space $\mathbb{R}^N$ together with the component-wise order, the meet and join operations are given by:

$$\forall i = 1, \ldots, N, (x \wedge y)_i = min\{x_i, y_i\};$$

$$\forall i = 1, \ldots, N, (x \vee y)_i = max\{x_i, y_i\}.$$

Other examples of lattices are depicted in Figure 4-1, sourced from Milgrom and Roberts (1994). The sets *S*, {*x*, *y*, $x \wedge y$, $x \vee y$}, {$x \wedge y$, $x \vee y$ }, and the four singletons are all lattices.

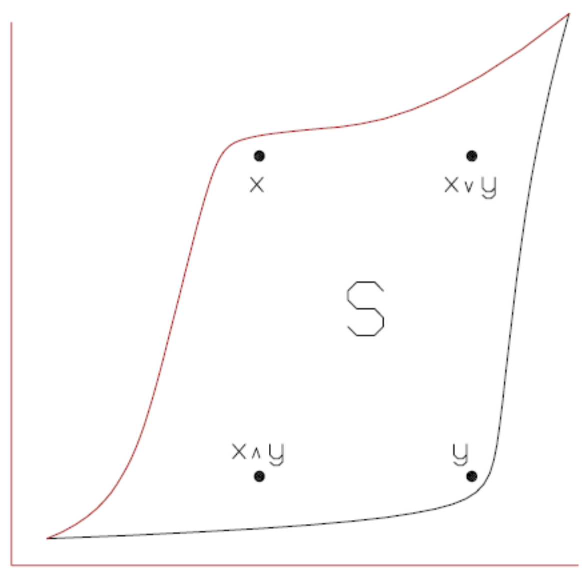


Figure 4-1: Examples of lattices in $\mathbb{R}^2$ (Milgrom and Roberts, 1994)

Constraining a choice *x* to lie in a lattice expresses a kind of "technical complementarity": "it says that increasing the value of some variables never prevents one from increasing the others as well (although it may actually require increasing some), and similarly that decreasing some variables never prevents decreasing others" (Milgrom and Roberts, 1995: 182).

According to Topkis (1995, 1998), Milgrom and Roberts (1990, 1995), and Milgrom and Shannon (1994), two variables x and y in a lattice X are complements if a real-valued function f (x,y) on the lattice X in $\mathbb{R}^N$ is supermodular in its arguments. In turn, a function f: $X \rightarrow \mathbb{R}$ is supermodular if and only if, for any x and y in X,

$$f(x) + f(y) \leq f(x \wedge y) + f(x \vee y). \tag{1}$$

The previous inequality is equivalent to:

$$f(x \vee y) - f(y) \geq f(x) - f(x \wedge y). \tag{2}$$

Recalling that for the Euclidean space $\mathbb{R}^N$ together with the component-wise order, the meet and join operations are given by:

$$\forall i = 1, \ldots, N, \ (x \wedge y)_i = \min \{x_i, y_i\}$$

$$\forall i = 1, \ldots, N, \ (x \vee y)_i = \max \{x_i, y_i\},$$

inequality (2) can be read as: the return from increasing some variables is greater the larger the values of other variables. Therefore, inequality (2) expresses, in mathematical terms, the nominal definition of complementarity given earlier (Milgrom and Roberts, 1994). Also, from the inequalities above, it is evident that complementarity is symmetrical: increasing x raises the value of increases in y and, symmetrically, increasing y raises the value of increases in x (Antonioli et al., 2013).

By subtracting $2f(x \wedge y)$ from both members of inequality (1), one obtains:

$$[f(x) - f(x \wedge y)] + [f(y) - f(x \wedge y)] \leq f(x \vee y) - f(x \wedge y). \tag{3}$$

Inequality (3) can be read as: the returns from increasing all the variables jointly are greater than the sum of the returns when the variables are increased separately. This reformulation makes it clear that complementary variables create super-additive value (Milgrom and Roberts, 1995; Barua and Whinston, 1998).

In the present work, a number of different approaches are adopted to investigate the presence of complementarities among OSC use, PM, and PKAC in building MCC, as explained in the next section.

4.1.2 Approaches to testing for complementarities

Consistent with prior literature on complementary organizational practices, the strategy of marshalling different types of evidence has been followed (Tambe et al., 2012). When they are consistent with the complementarity hypothesis, these different types of evidence, considered as a whole, strongly suggest the presence of complementarity between a set of organizational practices (Tambe et al., 2012). In particular, three different approaches, developed in the relevant literature, were applied in this research:

I. The "adoption" approach (Cassiman and Veugelers, 2006), also known as the "correlations and demand equations" approach (Brynjolfsson and Milgrom, 2012), which uses multiple regression analysis to examine whether a set of practices is more likely to be adopted jointly rather than separately (e.g., Arora 1996; Aral et al., 2012; Bryjolfsson and Milgrom, 2012);

II. The "performance equations" approach (Brynjolfsson and Milgrom, 2012), which uses multiple regression analysis to examine whether the performance outcome of adopting a set of practices together is greater than the sum of the performance outcomes when each practice is adopted separately (e.g., Arora 1996; Aral et al., 2012; Bryjolfsson and Milgrom, 2012);

III. The "second-order latent-factor" approach, which uses structural equation modelling (SEM) to compare the performance effects of the individual practices with the performance effects of the full system of practices (e.g., Tanriverdi and Venkatraman, 2005).

4.1.2.1 Adoption approach

The adoption approach determines if a set of practices is more likely to be adopted jointly rather than separately (e.g., Arora 1996; Aral et al., 2012; Brynjolfsson and Milgrom, 2013). Measuring the correlation of practices is perhaps the most common approach to testing for complementarities. If two practices are complementary, managers, in trying to maximize the benefits, will seek to adopt them together. Similarly, market competition might reduce or eliminate the population of firms that attempt to implement inefficient combinations of practices. In both cases, the fact that the practices co-vary provides evidence of complementarities. This suggests a test for complementarities using the correlation of practices:

$$K_c \equiv correlation\,(x, y).$$

A larger value of K_c provides more support to the hypothesis that the practices x and y are complementary. If other exogenous factors affect the choices on the practices x and y, then those factors should be conditional for this correlation. It is worth noting that this correlation test can be seen as estimating a demand equation: the demand for one practice, x, will be higher when the level of the other practice, y, is higher.

4.1.2.2 Performance equations approach

The performance equations approach uses performance differences to test for complementarities; that is, it examines whether the performance outcome of the hypothesized complementary practices when used together is greater than the sum of the performance outcomes when each practice is used separately (e.g., Arora 1996; Aral et al., 2012; Bryjolfsson and Milgrom, 2012). When the use of a practice is described by a dichotomous variable and the function *F* represents some performance outcome, then inequality (3) in Section 4.1.1 becomes:

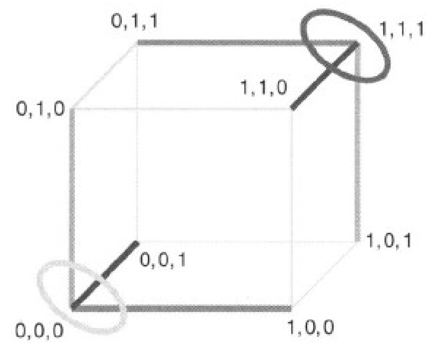
$$[F(1,0) - F(0,0)] + [F(0,1) - F(0,0)] \leq F(1,1) - F(0,0).$$

This inequality suggests the following statistic to test for complementarities using performance differences:

$$K_p \equiv F(1,1) + F(0,0) - F(1,0) - F(0,1).$$

When K_p is significantly greater than zero, then the hypothesis that the practices are complementary is supported.

This approach can be generalized for three or more dichotomous variables. In the case of three dichotomous variables, the complementarity theory suggests the use of four performance tests (Figure 4-1), which can be easily illustrated using a cube diagram (e.g. Aral et al., 2012; Tambe et al., 2012)



Four tests of complementarity:

1. $F(1,1,1)$ - $F(0,1,1) > F(1,0,0)$ - $F(0,0,0)$
2. $F(1,1,1)$ - $F(1,0,1) > F(0,1,0)$ - $F(0,0,0)$
3. $F(1,1,1)$ - $F(1,1,0) > F(0,0,1)$ - $F(0,0,0)$
4. $[F(1,1,1) - F(0,1,1)] + [F(1,1,1) - F(1,0,1)] + [\ F(1,1,1) - F(1,1,0\ ] - [F(1,0,0) - F(0,0,0)] - [F(0,1,0) - F(0,0,0)] - [F(0,0,1) - F(0,0,0)] > 0$

Figure 4-2: The cube view of three-way complementarities and the associated four tests of complementarity (Tambe et al., 2012)

The first three tests can be seen as comparisons among pairs of edges of a cube, where each axis (*X*, *Y*, *Z*) represents one of the three dichotomous variables (Aral et al., 2012; Tambe et al., 2012). For each variable, the value “1” denotes that the practice is present, while the value “0” denotes that the practice is absent. In the case of continuous variables, performing the tests requires dichotomizing the variables using the median value as a splitting criterion: “1” indicates a high value, above the median; and “0” indicates a low value, below the median. The fourth test simultaneously considers performance differences along all three pairs of edges.

For each of the four tests, the K_p statistic can be calculated from a regression of the performance *F* on the 8 dummy variables corresponding to all the possible combinations of the values of the three practices (A_{xyz}). For example, the dummy

A_{111} represents organizations that use all the three practices, while the dummy A_{100} represents organizations that use the practice "*X*" but not "*Y*" or "*Z*." The regression equation for the performance *F* is:

$$F(X,Y,Z) = B_0 + B_1A_{111} + B_2A_{011} + B_3A_{110} + B_4A_{101} + B_5A_{100} + B_6A_{010} + +B_7A_{001} + B_8A_{000} + \varepsilon.$$

Since

$$A_{000} = 1 - (A_{001} + A_{010} + A_{011} + A_{100} + A_{101} + A_{110} + A_{111}),$$

the regression equation becomes:

$$F(X,Y,Z) = B_0 + B_8 + (B_1 - B_8)A_{111} + (B_2 - B_8)A_{011} + (B_3 - B_8)A_{110} + (B_4 - B_8)A_{101} + (B_5 - B_8)A_{100} + (B_6 - B_8)A_{010} + (B_7 - B_8)A_{001} + \varepsilon,$$

which can be rewritten as:

$$F(X,Y,Z) = C_0 + C_1A_{111} + C_2A_{011} + C_3A_{110} + C_4A_{101} + C_5A_{100} + C_6A_{010} + C_7A_{001} + \varepsilon. \qquad (4)$$

Using the parameter estimates for equation (4), the values of the K_p statistic and of its standard error $SE(K_p)$ can be computed for each of the four tests reported in Figure 4-1.

The first test compares the magnitude of the performance difference for the edge from (0, 1, 1) to (1, 1, 1) with the performance difference for the edge from (0, 0, 0) to (1, 0, 0). Accordingly, the K_p statistic is defined as follows:

$$K_{p\,1} = F(1,1,1) - F(0,1,1) - F(1,0,0) + F(0,0,0).$$

A value of $K_{p\,1}$ greater than zero means that the use of practice *X* yields greater returns, in terms of performance *F*, in the presence of practices *Y* and *Z* than in the absence of the same practices. The hypothesis that $K_{p\,1}$ is significantly greater than zero can be tested using a one-tailed t-test, where the t value is calculated as follows:

$$t = \frac{\widehat{K}_{p1}}{SE\left(\widehat{K}_{p1}\right)}$$

Using equation (4), $K_{p\,1}$ is estimated as:

$$\widehat{K}_{p1} = C_0 + C_1 - (C_0 + C_2) > C_0 + C_5 - C_0$$

$$\rightarrow \widehat{K}_{p1} = C_1 - C_2 - C_5$$

and $SE(\widehat{K}_{p\,1})$ is estimated as:

$$SE\left(\widehat{K}_{p1}\right) = \sqrt{\widehat{V}(\widehat{K}_{p1})} =$$

$$= \sqrt{\widehat{V}(C_1) + \widehat{V}(C_2) + \widehat{V}(C_5) - 2\widehat{COV}(C_1C_2) - 2\widehat{COV}(C_1C_5) + 2\widehat{COV}(C_2C_5)},$$

where $\widehat{V}$ and $\widehat{COV}$ denote the sampling variance and covariance operators.

The second test compares the magnitude of the performance difference for the edge from (1, 0 ,1) to (1, 1 ,1) with the performance difference for the edge from (0, 0, 0) to (0, 1, 0). Accordingly, the K_p statistic is defined as follows:

$$K_{p\,2} = F(1,1,1) - F(1,0,1) - F(0,1,0) + F(0,0,0).$$

Using equation (4), $K_{p\,2}$ is estimated as:

$$\widehat{K}_{p2} = C_0 + C_1 - (C_0 + C_4) > C_0 + C_6 - C_0$$

$$\rightarrow \widehat{K}_{p2} = C_1 - C_4 - C_6$$

and $SE(\widehat{K}_{p\,2})$ is estimated as:

$$SE\left(\widehat{K}_{p2}\right) =$$

$$= \sqrt{\widehat{V}(C_1) + \widehat{V}(C_4) + \widehat{V}(C_6) - 2\widehat{COV}(C_1C_4) - 2\widehat{COV}(C_1C_6) + 2\widehat{COV}(C_4C_6)}.$$

A value of $K_{p\,2}$ greater than zero means that the use of practice *Y* yields greater returns, in terms of performance *F*, in the presence of practices *X* and *Z* than in the absence of the same practices.

The third test compares the magnitude of the performance difference for the edge from (1, 1 ,0) to (1, 1 ,1) with the performance difference for the edge from (0, 0, 0) to (0, 0, 1). Hence, the K_p statistic is defined as follows:

$$K_{p\,3} = F(1,1,1) - F(1,1,0) - F(0,0,1) + F(0,0,0).$$

Using equation (4), $K_{p\,3}$ is estimated as:

$$\widehat{K}_{p3} = C_0 + C_1 - (C_0 + C_3) > C_0 + C_7 - C_0$$

$$\rightarrow \widehat{K}_{p3} = C_1 - C_3 - C_7$$

and $SE(\widehat{K}_{p\,3})$ is estimated as:

$$SE(\widehat{K}_{p3}) =$$

$$= \sqrt{\hat{V}(C_1) + \hat{V}(C_3) + \hat{V}(C_7) - 2\widehat{COV}(C_1C_3) - 2\widehat{COV}(C_1C_7) + 2\widehat{COV}(C_3C_7)}.$$

A value of $K_{p\,3}$ greater than zero means that the use of practice *Z* yields greater returns, in terms of performance *F*, in the presence of practices *X* and *Y* than in the absence of the same practices.

The fourth test estimates the three-way complementarities. It simultaneously compares the magnitude of the performance difference for the edges from (0, 1, 1), (1, 0, 1), and (1, 1 ,0) to (1, 1 ,1) with the performance differences for the edges from (0, 0, 0) to (1, 0, 0), (0, 1, 0), and (0, 0, 1). Accordingly, the $K_{p\,4}$ statistic is defined as follows:

$$K_{p\,4} = F(1,1,1) - F(0,1,1) + F(1,1,1) - F(1,0,1) + F(1,1,1) - F(1,1,0) - F(1,0,0) \\ + F(0,0,0) - F(0,1,0) + F(0,0,0) - F(0,0,1) + F(0,0,0).$$

Using equation (4), $K_{p\,4}$ is estimated as:

$$\widehat{K}_{p4} = (C_0 + C_1) - (C_0 + C_2) + (C_0 + C_1) - (C_0 + C_4) + (C_0 + C_1) - (C_0 + C_3)$$
$$> C_0 + C_5 - C_0 + C_0 + C_6 - C_0 + C_0 + C_7 - C_0$$

$$\rightarrow \widehat{K}_{p4} = 3C_1 - (C_2 + C_3 + C_4 + C_5 + C_6 + C_7)$$

and $SE(\widehat{K}_{p\,4})$ is estimated as:

$$SE(\widehat{K}_{p\,4}) =$$

$$= \sqrt{9\hat{V}(C_1) + \sum_{i=1}^{7} \hat{V}(C_i) - 6(\sum_{i=1}^{7} \widehat{COV}(C_1 C_i)) + 2(\sum_{i=2}^{7} \sum_{j=3}^{7} \widehat{COV}(C_i C_j))}.$$

As mentioned above, these four tests of complementarities can be used for continuous variables as well, provided they are dichotomized. However, dichotomizing them inevitably causes loss of information. An alternative is to test complementarities between continuous variables using the so-called "productivity test" (Aral et al., 2012), which also relies on performance equations. In the case of three continuous variables, for example, the following performance equation will be estimated:

$$F(X,Y,Z) = \beta_0 + \beta_x X + \beta_y Y + \beta_z Z + \beta_{xy} X Y + \beta_{xz} X Z + \beta_{yz} Y Z + \beta_{xyz} X Y Z + \varepsilon,$$

where X, Y, and Z are all standardized.

A positive and significant value of the standardized coefficient for the three-way interaction term (β_{xyz}) suggests that the three practices form a system of complements. However, it must be stressed that a positive and statistically significant β_{xyz} is a necessary but not sufficient condition for three-way complementarities (Tambe et al., 2012). This is because, when using standardized measures, a high value for the three-way term can correspond not only to the combination of high values for all three variables but also to any of the three high-low-low combinations. For this reason, other conditions must be verified before concluding that the three practices are complementary. Specifically, output elasticity with respect to each variable must increase when the values of the other two are high (Tambe et al., 2012). For example, from the previously estimated regression equation, output elasticity with respect to *X* is given by:

$$\eta_x = \frac{\partial F(X,Y,Z)}{\partial X} = \beta_x + \beta_{xy} Y + \beta_{xz} Z + \beta_{xyz} YZ.$$

One possibility is to examine the variation of η_x as each of the other two variables (*Y* and *Z*) is increased separately. For instance, η_x is an increasing function of *Y* if the following condition is met:

$$\frac{\partial \eta_x}{\partial Y} = \beta_{xy} + \beta_{xyz} Z > 0.$$

This condition is satisfied if:

$$Z > -\frac{\beta_{xy}}{\beta_{xyz}}$$

Therefore, if *Z* is above this threshold value, the marginal return to an increase in *X* is an increasing function of *Y.*

Likewise, for η_x to be an increasing function of *Z*, the following condition must be met:

$$Y > -\frac{\beta_{xz}}{\beta_{xyz}}.$$

Similar conditions can be derived for η_Y and η_Z.

However, complementarity conditions can also be formulated for simultaneous movements of *Y* and *Z* from 0 to *G*. In this case, output elasticity with respect to *X* becomes a function of *G*:

$$\eta_x(G) = \frac{\partial F(X,Y,Z)}{\partial X}\Big|_{Y=G,\, Z=G} = \beta_x + (\beta_{xy} + \beta_{xz})G + \beta_{xyz} G^2$$

and the complementary condition becomes:

$$\frac{\partial \eta_x}{\partial G} = \beta_{xy} + \beta_{xz} + 2G\beta_{xyz} > 0.$$

This condition is satisfied if:

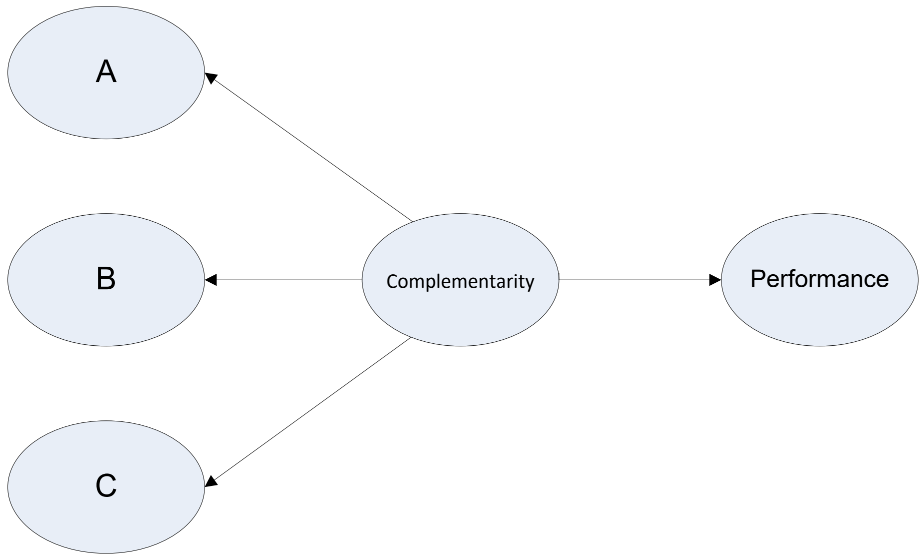
$$G > -\frac{\beta_{xy}+\beta_{xz}}{2\beta_{xyz}}.$$

Thus, if both *Y* and *Z* are greater than this threshold, the marginal increment of *F(X,Y,Z)* with respect to *X* increases with the simultaneous increment of *Y* and *Z*.

4.1.2.3 Second-order latent-factor approach

A second-order factor is an unobservable factor that manifests or reflects itself through a number of first-order factors (Williams et al., 2004). A formative second-order factor does not assume any interaction or covariance among the first-order factors (Chin 1998), while a reflective second-order factor captures patterns of interactions and covariance among the first-order factors (Rindskopf and Rose, 1988). Given the high level of multilateral interactions and covariance among complementary variables (Milgrom and Roberts, 1990, 1995), Tanriverdi and Venkatraman (2005) proposed that a reflective second-order factor is appropriate for capturing complementarities among first-order variables.

Therefore, the second-order latent-factor approach models complementarity as a reflective second-order factor that accounts for the covariance among first-order factors. But to assess whether returns from a set of complementary variables are greater than the sum of returns from the individual variables, it is necessary to compare the performance effects of the set of complementary variables with the performance effects of the individual variables (Ichniowski et al., 1997; Whittington et al., 1999). Accordingly, the second-order latent-factor approach compares the second-order model mentioned above with a first-order model that hypothesizes that the individual variables have independent effects (Figure 4-3).



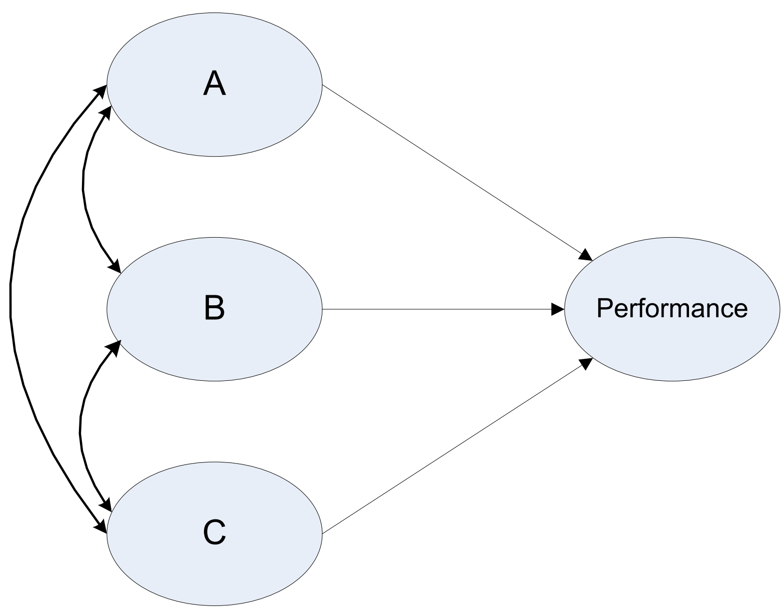


Figure 4-3: Complementarity model and independent-effects model for three variables

4.1.2.4 Rationale for the triangulation of the adopted approaches

This section aims to explain the logic underlying the choice of testing for the complementarities between OSC use, PM, and PKAC using the three approaches described above. First, I will discuss the advantages of triangulating the two approaches that are based on regression analysis (i.e., the adoption and performance approaches). Subsequently, I will present the differences between these two "regression-based" approaches and the second-order latent-factor approach, which relies on structural equation modeling (SEM).

Combining the adoption and performance approaches to test for complementarities between organizational practices is very useful (Brynjolfsson and Milgrom, 2012), as each of the two tests tends to be stronger when the other is weaker (Aral et al., 2012). On the one hand, if all managers were aware that a particular set of practices is complementary, then it would be logical to expect that companies tend to apply such practices together. Consequently, the correlations among these practices would be nearly perfect. If these practices were always adopted jointly, however, it would be impossible to detect performance differences due to varying combinations of these practices and, therefore, the performance equations approach would fail. Conversely, if managers had no understanding of the complementarities between the same practices, these practices could show no correlation, while the statistical power of the performance tests would be maximized (Aral et al., 2012). In other words, the correlation between practices could depend on the extent to which managers understand and embrace their complementarities, while the power of performance tests is contingent upon the extent to which the practices vary randomly (Tambe et al., 2012). Since most of the practical cases lie somewhere in between perfect correlation among practices and random and independent adoption of the same practices, the triangulation of the two approaches appears appropriate to investigate complementarities between practices.

As mentioned before, both the adoption and performance equation approaches use regression analysis, while the second-order latent-factor approach relies on SEM. The fundamental drawback of using SEM instead of regression analysis is that one cannot test for the conditions concerning output elasticity that derive from the definition of complementarity. However, regression analysis assumes that the independent variables are error free; that is, it assumes perfect measures of the independent variables. In addition, regression analysis requires a single measure for each variable. Consequently, if a variable is originally measured using a multi-item scale, this variable should be recalculated as a single item, for example by using a summated scale. Instead, SEM models measurement errors and incorporates both unobserved (i.e., latent) and observed variables. A latent variable is usually measured with a multi-item scale, where its items are the observed variables, and SEM models measurement errors for each of those items. In this manner, the estimates for the path coefficients in the structural model are not influenced by measurement errors. Another advantage of the second-order latent-factor approach, as compared with the adoption approach, is that the former not only permits modeling the covariation among the putative complements but also testing for the performance outcome of their covariation. In addition, the use of a second-order latent factor allows for modeling covariation patterns that could be problematic for regression analysis due to multicollinearity issues, and this is another advantage with respect to the performance equations approach.

In summary, each of the three abovementioned approaches has pros and cons that are, somehow, complementary, and this justifies triangulation of those approaches. As noted by Tosi and Slocum (1984: 16), “statistical techniques have frustrated researchers’ attempts to test for the interaction effects being modeled because each technique has implied biases. Researchers need to compare the utility of each of these statistical techniques using the same data set.”

4.2 Data description

The data used to test the hypothesis were collected in the fourth round of the High-Performance Manufacturing (HPM) international research project (cf. Schroeder and Flynn, 2001). The aim of this project is to comprehensively assess a manufacturing plant's operations and their impact on plant performance (Wang et al., 2018). In the fourth round of the project (data collection completed in 2017), the sample included 330 mid- to large-sized manufacturing plants in the machinery, electronics, and transportation equipment industries. The plants were located in Brazil, China, Taiwan, Japan, South Korea, Vietnam, Germany, the UK, Finland, Sweden, Italy, Spain, Israel, the US, and Austria/Switzerland. In return for participation, each plant was promised a detailed report comparing its operations to those of other plants in the same industry. As a result, the response rate was approximately 65% in each country (Danese et al., 2019). Each participating plant received 12 different hardcopy questionnaires covering different topics (Table 4-1). For each questionnaire, each plant was asked to identify two respondents considered the most knowledgeable about the constructs covered by the questionnaire, with the only exception of the accounting questionnaire, which was administered to only one respondent. The cover sheet of each questionnaire reported, besides the title of the questionnaire, some examples of job titles of potential respondents deemed appropriate by the HPM researchers (Table 4-1).

Table 4-1: Questionnaires and job titles of potential respondents

Questionnaire	Examples of job titles of potential respondents	Number of respondents
Accounting	Plant accountant, accounting controller, accounting director	1
Downstream supply chain management	Logistics manager, sales manager, marketing manager, customer relationship manager, after sales service manager, supply chain manager	2
Environmental affairs	Environmental affairs director, environmental quality and safety manager	2
HR management	Human resource manager, human resource management director	2
Information system management	Chief information officer, IT manager, IS manager	2
Plant management	Plant manager, CEO, chief operating officer	2
Process engineering	Process engineering, production manager	2
New product development	Product development manager, product engineer, product designer	2
Quality management	Quality manager, quality control manager	2
Supervision	Supervisor	2
Upstream supply chain management	Purchasing manager, buyer, logistics manager, supply chain manager	2
Production control	Inventory manager, production manager, production planning and control manager	2

The measurement items for the focal constructs in the present study were taken from the information system management, new product development, downstream supply chain management, and process engineering questionnaires. The dataset included missing values for the focal constructs. Where possible, mean replacement across the items of the same scale (Roth et al., 1999) was used for the missing values included in the measures of OSC use, PM, PKAC, and MCC. Where this was not possible, list-wise deletion was applied. As a result, the final sample included 215 observations. The distributions of these observations by country and by industry are reported in Table 4-2. The median value of the number of plant employees in the final sample is 353.

Table 4-2: Sample distribution by country (a) and by industry (b)

Country	**Number**	**%**
BRA	9	4.19
CHN	19	8.84
ESP	16	7.44
FIN	12	5.58
GER	20	9.30
ISR	5	2.33
ITA	25	11.63
JPN	18	8.37
KOR	21	9.77
SWE	3	1.40
AUT/SWI	10	4.65
TWN	23	10.70
UK	13	6.05
US	7	3.26
VIE	14	6.51
Total	215	100.00

(a)

Industry	**Number**	**%**
Machinery	69	32.09
Electronics	88	40.93
Transportation equipment	58	26.98
Total	215	100.00

(b)

4.3 Measurement of the focal constructs

Measurement items used in this research are presented in Table 4-1. Multi-item scales were used for the focal constructs. Where possible, validated measurement scales were adopted. The PM construct was measured using the three-item scale adapted from Forza et al. (2000) and validated by Liu et al. (2010). A five-item scale from Huang et al. (2008) was used to measure MCC. For PKAC, a new scale was developed using items that capture the extent to which a manufacturing organization learns from its customers in terms of product knowledge. The items of this scale capture all three processes necessary for knowledge absorption from customers, namely eliciting knowledge from customers, assimilating that knowledge, and applying that knowledge (Zhang et al., 2015a). Principal component analysis showed that these items load on only one factor with an eigenvalue greater than 1.0, with factor loadings above 0.7 and a Cronbach's alpha value of 0.84. The measure for OSCs captures the extent to which a plant enables its customers to configure products online as well as the degree to which the plant is capable of providing customers with dynamic pricing offers during product configuration. Principal component analysis showed that two items load on only one factor with an eigenvalue greater than 1.0, factor loadings above 0.7, and a Cronbach's alpha value of 0.81.

Table 4-3: Measurement items and confirmatory factor analysis (CFA) results for the measurement model

Construct	Measuring item	Standard. factor loading [a]
Online sales configurator [i]	*For which of the following marketing and sales activities does your plant use the Internet or EDI? (1 = Not at all, …, 5 = Completely)*	
composite reliability (CR) = 0.82, average variance extracted (AVE) = 0.69	- Providing online customized customer service, where customers can configure the product within the constraints stated by the plant (mean (M)=2.26, standard deviation (SD)=1.302)	0.75
	- Providing dynamic pricing offers to potential buyers (M=2.18, SD=1.247)	0.91
Product modularity [ii] CR = 0.76, AVE = 0.52	*Please indicate the extent to which you agree or disagree with each of the following statements about product development projects in your plant. (1 = Strongly disagree, …, 5 = Strongly agree)*	
	- Our products are modularly designed, so they can be rapidly built by assembling modules (M=3.45, SD=1.076)	0.83
	- We have defined product platforms as a basis for future product variety and options (M=3.84, SD=0.903)	0.52
	- Our products are designed to use many common modules (M=3.84, SD=0.933)	0.77
Product knowledge absorption from customers [iii]	*Please indicate the extent to which you agree or disagree with each of the following statements about your plant. (1 = Strongly disagree, …, 5 = Strongly agree)*	
CR = 0.85, AVE = 0.59	- We obtain a great amount of our product knowledge from our customers (M=3.64, SD=0.958)	0.82
	- Our customers provide us with valuable information on product innovation (M=3.72, SD=0.857)	0.81
	- We have learned a lot from our customers as part of our product development process (M=3.75, SD=0.896)	0.81
	- We systematically check whether we have applied the knowledge we acquire from our customers regarding our products (M=3.37, SD=0.948)	0.61

Mass-customization capability [iv] CR = 0.8, AVE = 0.45	*Please indicate the extent to which you agree or disagree with each of the following statements about your plant. (1 = Strongly disagree, …, 5 = Strongly agree)*	
	- We are highly capable of large-scale product customization (M=3.61, SD=0.980)	0.68
	- We can easily add significant product variety without increasing cost (M=3.41, SD=0.954)	0.67
	- We can customize products while maintaining high volume (M=3.65, SD=0.957)	0.76
	- We can add product variety without sacrificing quality (M=3.95, SD=0.813)	0.43
	- Our capability for responding quickly to customization requirements is very high (M=3.90, SD=0.900)	0.77
Model fit indices: $\chi 2$ (df) = 131.5 (71), $\chi 2$/df = 1.85; Tucker-Lewis coefficient (TLI) = 0.93, comparative fit index (CFI) = 0.94, incremental fit index (IFI) = 0.94, root mean square error of approximation (RMSEA) = 0.063 (0.046 – 0.08)		

[a] All factor loadings are significant at $p < 0.001$

[i] Questionnaire: information system management. For the roles of respondents, see Table 4-1.

[ii] Questionnaire: new product development. For the roles of respondents, see Table 4-1.

[iii] Questionnaire: downstream supply chain management. For the roles of respondents, see Table 4-1.

[iv] Questionnaire: process engineering. For the roles of respondents, see Table 4-1.

4.4 Focal constructs measurement quality assessment

4.4.1 Reliability and validity

The psychometric properties of the measurement scales for the four latent constructs of interest were estimated by performing confirmatory factor analysis (CFA) (Gerbing and Anderson, 1988) within the IBM SPSS Amos v22 software package.

For convergent validity evaluation, a model was created in which each of the measurement scale items was restricted to loading only on the construct it was intended to measure. In this model, the four latent constructs were free to correlate. The model fit with the data was good, as indicated by the values of the typical fit indices: $\chi 2$ (df) = 131.5 (71), $\chi 2$/df = 1.85; Tucker-Lewis coefficient (TLI) = 0.93, comparative fit index (CFI) = 0.94, incremental fit index (IFI) = 0.94, root mean square error of approximation (RMSEA) = 0.063 (0.046 – 0.08). Furthermore, for all items, standardized factor loadings were positive, significant at $p < 0.001$, and above 0.50 (Gerbing and Anderson, 1988; Bollen, 1989). The only exception is one item of the MCC scale whose standardized factor loading was below 0.50. Since this item captures an important characteristic of the underlying construct, it was decided to keep it, just as Peng et al. (2011) did with their "supplier collaboration IT" scale. Altogether, these results suggest acceptable convergent validity (Anderson and Gerbing, 1988; Gerbing and Anderson, 1988; Menor and Roth, 2007).

Average variance extracted (AVE) and composite reliability (CR) were used to assess reliability. The calculated values for CR and AVE are reported in Table 4-1. All CR values were above 0.70, and all AVE scores exceeded 0.50, except for the MCC scale, whose AVE score was 0.45. However, this AVE score is similar to those that can be found in several previous studies on MCC (0.40 [Kristal et al., 2010], 0.42 [Huang et al., 2010,] and 0.43 [Salvador et al., 2015]). In summary, these results indicated acceptable reliability levels (Fornell and Larcker, 1981; O'Leary-Kelly and Vokurka, 1998).

Discriminant validity was evaluated using Fornell and Larcker's (1981) procedure. For each of the four latent constructs, the square root of the AVE exceeds the correlations with the other latent constructs in the model (Table 4-2). This is an indication of good discriminant validity for adopted measurement scales.

Table 4-4: Discriminant validity

Variable	Square root of AVE	Correlations			
		MCC	PM	OSC	PKAC
MCC	0.67	1.00			
PM	0.72	0.26	1.00		
OSC	0.83	0.15	0.19	1.00	
PKAC	0.77	0.24	0.16	0.09	1.00

4.4.2 Common method bias

In the present research, common method bias (CMB) could be a concern because self-report measures are involved (Spector, 2006). However, the concerns about CMB are reduced in this case because the respondents are different for the predictors and the outcome variable (Podsakoff et al., 2003).

Nonetheless, Harman's single-factor test was performed through both exploratory factor analysis and CFA as statistical controls for CMB. The exploratory factor analysis with the unrotated factor solution was conducted, and the analysis did not produce a single general factor. In addition, the first factor did not explain the majority of the covariance among the measures (Podsakoff et al., 2003). Further, CFA was used to test the hypothesis that a single factor accounted for all of the variance in the present data (Podsakoff et al., 2003). The fit of this model with the data was poor ($\chi2$ (df) = 436.5 (76), $\chi2$/df = 5.75; TLI = 0.59, CFI = 0.66, IFI = 0.66, RMSEA = 0.150). According to these results, CMB does not appear to be a concern in this study.

4.5 Control variables

The economic environments of different countries as well as the technology availability in different types of industry might influence the companies' MCC (Liu et al., 2006). Also, company size might affect MCC development, since large companies have more possibility to invest simultaneously in multiple operational priorities to resolve performance trade-offs (Huang et al., 2008; Zhang et al, 2014). Thus, plant size, country, and industry were included as control variables (Liu et al., 2006; Huang et al., 2008; Zhang et al., 2014) in all the analyses except the ones using SEM, as the inclusion of 14 country dummies would require a larger sample in that case (Byrne, 2010). Plant size was measured as the natural log of the overall number of people employed (e.g., Haig and Peng, 2010). Countries and industries were introduced as dummy variables.

5. Results

5.1 Adoption approach

5.1.1 Correlation test

In the adoption approach, the existence of complementarity among the putative complements OSC, PM, and PKAC is tested through multiple linear regression. Each of the following tables reports the results of three multiple regression analyses, where one of the three hypothesized complements is regressed on another while controlling for the effects of plant size, country, and industry: the first regression (Column A) is performed on the full sample; the other two regressions are performed on the subsamples with a positive (Column B) and a negative (Column C) value, respectively, for the third putative complement. The sample is split based on the average value of the third hypothesized complement. All variables are standardized except industry and country.

Table 5-1: Three-way correlations – Linear regression of PKAC on PM

	A all obs.	B OSC > 0	C OSC ≤ 0
Dependent variable	PKAC	PKAC	PKAC
PM	0.09 (*p* = 0.191)	0.32 (*p* = 0.003)	- 0.02 (*p* = 0.810)
Number of observations	215	88	127
Control variables	country, industry, size	country, industry, size	country, industry, size
R^2	0.25	0.35	0.33

Table 5-1 shows the pairwise correlations between PM and PKAC. The correlation between PM and PKAC is positive but not significant when the full sample of plants is used (Column A). In the split samples, the correlation between PM and PKAC remains non-significant when OSC use is low (Column C), while it is positive and highly significant when OSC use is high (Column B), suggesting that PM and PKAC are complements in the presence of OSC use. This result is consistent with the three-way complementarity hypothesis and its implication that the three putative complements are more likely to be adopted jointly rather than separately. Overall, results reported in Table 5-1 suggest the importance of examining the complete system of putative complements together, that is, to examine the so-called "three-way correlations," namely pairwise correlations in the subsamples instead of pairwise correlations in the full sample. As the results reported in Table 5-1 well exemplify, pairwise correlations in the full sample can be misleading (Aral et al., 2012).

Table 5-2: Three-way correlations – Linear regression of OSC on PKAC

	A all obs.	B PM > 0	C PM ≤ 0
Dependent variable	OSC	OSC	OSC
PKAC	0.018 (p = 0.813)	0.17 (p = 0.097)	- 0.07 (p = 0.535)
Number of observations	215	103	112
Control variables	country, industry, size	country, industry, size	country, industry, size
R^2	0.28	0.43	0.42

A similar pattern of results appears in Table 5-2. The pairwise correlation between OSC use and PKAC is statistically significant only when plants also have high PM (Column B). In the full sample and in the split sample where PM is low, the correlation between OSC use and PKAC is not statistically significant. These results suggest that OSC use and PKAC are complements only in the presence of PM and that the three putative complements are more likely to be adopted jointly rather than separately.

Table 5-3: Three-way correlations – Linear regression of PM on OSC

	A all obs.	B PKAC > 0	C PKAC ≤ 0
Dependent variable	PM	PM	PM
OSC	0.11 (p = 0.156)	0.12 (p = 0.282)	0.16 (p = 0.156)
Number of observations	215	117	98
Control variables	country, industry, size	country, industry, size	country, industry, size
R^2	0.2	0.33	0.33

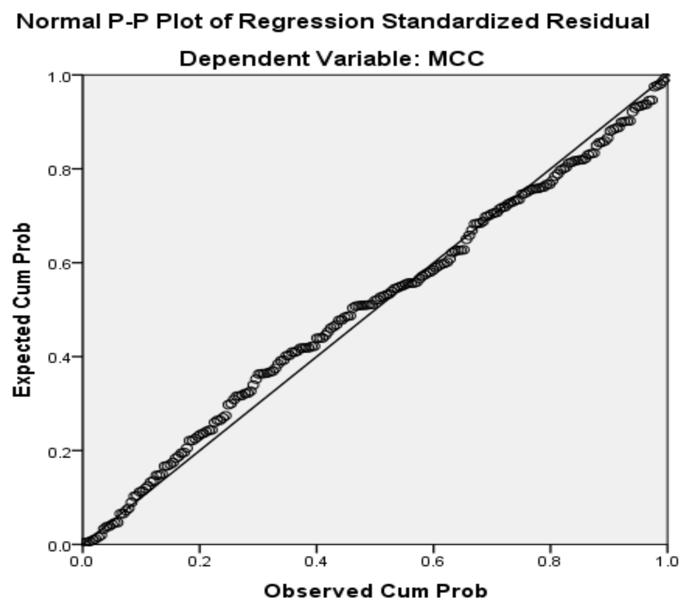
A slightly different picture is provided by Table 5-3, as the pairwise correlations between OSC use and PM are never statistically significant, including the case of the split sample with high PKAC. Thus, while the patterns of correlations presented in Tables 5-1 and 5-2 are consistent with the hypothesis of three-way complementarities among OSC use, PM, and PKAC, the results reported in Table 5-3 do not seem consistent with that hypothesis. However, it must be stressed that a positive correlation is neither necessary nor sufficient evidence of complementarities (Arora, 1996; Athey and Stern, 1998). Also, it should be recalled that managers' awareness of the benefits deriving from the joint implementation of a set of practices influences the level of correlations between those practices.

In summary, the results of the correlation tests should not be seen as evidence for the existence or nonexistence of complementarities but as preliminary evidence about whether managers perceive certain practices as being mutually beneficial. Managers may not have been sufficiently well informed to choose output-enhancing combinations of practices (Carree et al., 2011: 263). Moreover, financial constraints or other considerations may also influence their decisions.

5.2 Performance equations approach

5.2.1 Productivity test

The productivity test was carried out using multiple linear regression analysis. One assumption of this analysis is that the residuals are normally distributed. The analysis of the standardized residuals from the hierarchical moderated regression that includes all variables (Model 4 in Table 5-4) revealed no violation of the normality assumption (the Shapiro-Wilk test was non-significant at $p = 0.141$). Also, normal probability-probability (P-P) and quantile-quantile (Q-Q) plots show that the residuals are normally distributed (Figure 5-1).



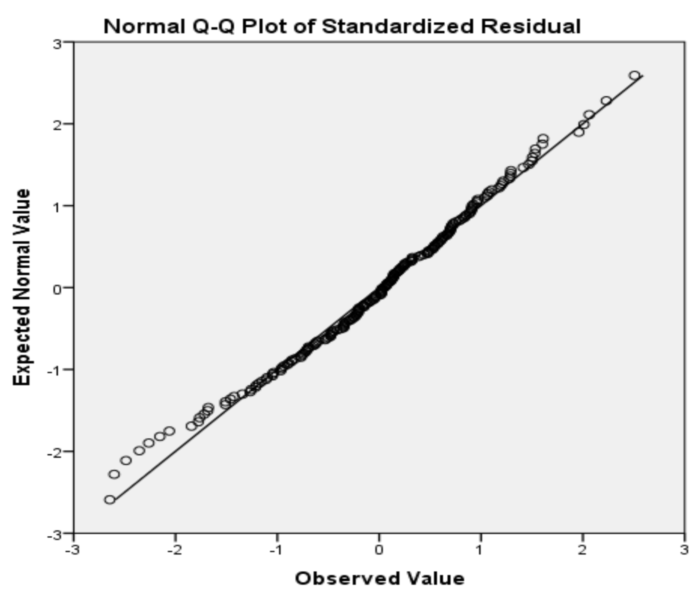


Figure 5-1: P-P and Q-Q plots

Further, multiple regression analysis assumes that the independent variables are not correlated with each other. An evaluation of variance inflation factor (VIF) values indicated no problems of multicollinearity. The greatest VIF value was 2.12 and the average of the VIF values was 1.58, while tolerances were all above 0.2 (Table 5-4) (see Field, 2009).

Finally, multiple linear regression analysis assumes homoscedasticity, which means that the variance in error terms is constant across the values of the independent variables. A scatterplot of standardized residuals versus predicted values showed equal distribution of residuals across all values of the independent variables (Figure 5-2).

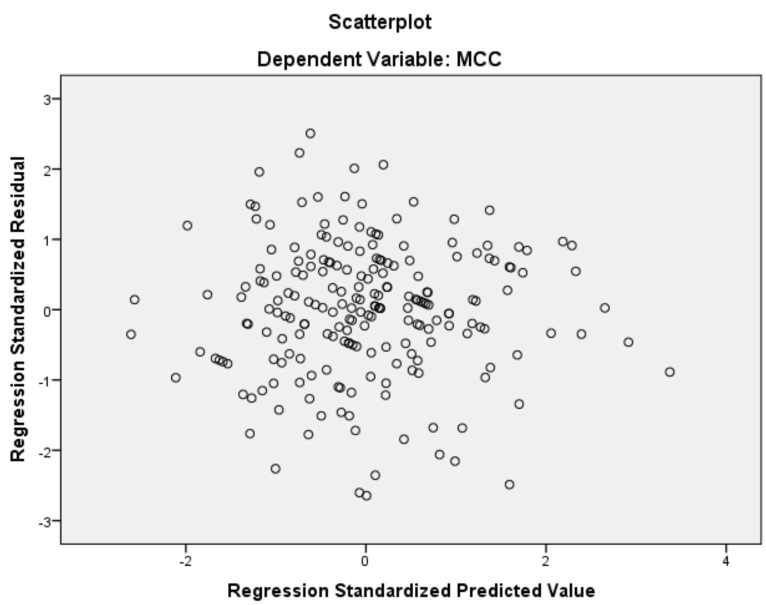


Figure 5-2: Scatterplot of standardized residuals versus predicted values

The performance equations approach required performing a hierarchical moderated multiple regression analysis that has MCC as the dependent variable. All random variables were standardized. The results of this analysis are reported in Table 5-4.

Table 5-4: Hierarchical multiple regression analysis results

	Model 1		*Model 2*		*Model 3*		*Model 4*		
	β	*p*	*β*	*p*	*β*	*p*	*β*	*p*	*VIF*
Constant	3.652	0.000	3.669	0.000	3.697	0.000	3.692	0.000	
Machinery industry	-0.034	0.663	-0.020	0.789	-0.026	0.725	-0.016	0.833	1.488
Transportation equipment industry	-0.112	0.170	-0.101	0.192	-0.126	0.107	-0.120	0.125	1.600
BRA	-0.055	0.472	-0.087	0.239	-0.076	0.300	-0.090	0.223	1.427
CHN	0.020	0.811	-0.059	0.473	-0.106	0.211	-0.126	0.140	1.922
ESP	0.068	0.403	0.058	0.456	0.051	0.518	0.045	0.566	1.624
FIN	0.043	0.579	0.000	0.999	-0.002	0.981	-0.004	0.962	1.458
GER	0.099	0.256	0.160	0.058	0.146	0.082	0.134	0.111	1.861
ISR	0.025	0.727	0.079	0.262	0.067	0.342	0.044	0.536	1.364
JPN	0.021	0.818	0.076	0.388	0.059	0.501	0.062	0.475	2.017
KOR	0.071	0.415	0.102	0.227	0.101	0.233	0.100	0.237	1.878
SWE	-0.049	0.481	-0.028	0.667	-0.031	0.640	-0.051	0.456	1.221
AUT/SWI	0.137	0.072	0.157	0.036	0.173	0.022	0.157	0.037	1.488
TWN	0.148	0.113	0.085	0.345	0.074	0.411	0.072	0.418	2.119
UK	-0.236	0.003	-0.278	0.000	-0.276	0.000	-0.288	0.000	1.596
USA	0.107	0.144	0.070	0.320	0.061	0.395	0.056	0.436	1.361
VIE	0.164	0.043	0.082	0.317	0.043	0.610	0.044	0.594	1.837
SIZE	-0.023	0.776	-0.069	0.366	-0.073	0.341	-0.083	0.275	1.547
OSC			0.031	0.677	0.032	0.685	-0.003	0.971	1.716
PM			0.208	0.003	0.170	0.018	0.171	0.017	1.346
PKAC			0.266	0.000	0.301	0.000	0.306	0.000	1.479
PM x OSC					-0.039	0.603	-0.078	0.309	1.576
PKAC x OSC					0.141	0.048	0.139	0.050	1.327
PKAC x PM					0.093	0.181	0.122	0.087	1.339
OSCxPMxPKAC							0.130	0.074	1.393
R^2	0.16		0.26		0.28		0.29		
ΔR^2	0.16 (p = 0.007)		0.1 (p = 0.000)		0.02 (p = 0.141)		0.01 (p = 0.074)		
F	2.148 (p = 0.007)		3.312 (p = 0.000)		3.158 (p = 0.000)		3.169 (p = 0.000)		

Model 1 contains only the control variables, that is, plant size, country, and industry. Model 2 adds the effects of OSC, PM, and PKAC on MCC to Model 1, without considering interaction effects. Model 3 adds all the pairwise interactions among OSC, PM, and PKAC to Model 2. Finally, the three-way interaction term between OSC, PM, and PKAC is included in Model 4.

The results for Model 4 show that the interaction effect of OSC and PKAC and the interaction effect of PM and PKAC are positive and statistically significant. Since OSC, PM, and PKAC are all standardized, a two-way interaction is to be interpreted as a conditional interaction effect at the mean value of the variable not involved in the interaction (Aiken and West, 1991). Applied to the results for Model 4, this means that OSC and PKAC mutually reinforce their positive effects on MCC when PM is at its mean value and, similarly, PM and PKAC mutually amplify their positive effects on MCC when OSC use is at its mean value. Instead, the interaction effect of PM and OSC is not statistically different from zero. This means that, at least when PKAC is at its mean value, PM and OSC do not have complementary effects on MCC. Finally, and most interesting, the standardized regression coefficient for the three-way interaction term is positive and statistically significant. As observed in Section 4.1.2.2, a positive and statistically significant regression coefficient for the three-way interaction term is a necessary but not sufficient condition for proving the existence of three-way complementarities. Therefore, to show that OSC, PM, and PKAC are complements, it should be demonstrated that the output elasticity with respect to each of these three variables increases when the values of the other two variables are high (Tambe et al., 2012). As explained in Section 4.1.2.2, this condition can be assessed either by examining the variation of the output elasticity with respect to X (η_x) as each of the other two variables (Y and Z) is increased separately (Table 5-5) or by examining the variation of η_x for simultaneous movements of Y and Z from 0 to G (Table 5-6).

Table 5-5: Conditions for complementarities considering the movement of one variable at a time

X = PM $\beta_{yz} = 0.133$ Y = PKAC $\beta_{xyz} = 0.143$ ***Z*** **= OSC** $Z > -0.938$	The marginal return (in terms of MCC) from an increase in PM is an increasing function of PKAC, provided that the standardized value of OSC use is greater than -0.938
X = PKAC $\beta_{yz} = 0.133$ Y = PM $\beta_{xyz} = 0.143$ ***Z*** **= OSC** $Z > -0.938$	The marginal return (in terms of MCC) from an increase in PKAC is an increasing function of PM, provided that the standardized value of OSC use is greater than -0.938
X = PKAC $\beta_{yz} = 0.131$ Y = OSC $\beta_{xyz} = 0.143$ ***Z*** **= PM** $Z > -1.069$	The marginal return (in terms of MCC) from an increase in PKAC is an increasing function of OSC, provided that the standardized value of PM is greater than -1.069
X = OSC $\beta_{yz} = 0.131$ Y = PKAC $\beta_{xyz} = 0.143$ ***Z*** **= PM** $Z > -1.069$	The marginal return (in terms of MCC) from an increase in OSC is an increasing function of PKAC, provided that the standardized value of PM is greater than -1.069
X = OSC $\beta_{yz} = -0.098$ Y = PM $\beta_{xyz} = 0.143$ ***Z*** **= PKAC** $Z > 0.600$	The marginal return (in terms of MCC) from an increase in OSC is an increasing function of PM, provided that the standardized value of PKAC is greater than 0.600
X = PM $\beta_{yz} = -0.098$ Y = OSC $\beta_{xyz} = 0.143$ ***Z*** **= PKAC** $Z > 0.600$	The marginal return (in terms of MCC) from an increase in PM is an increasing function of OSC, provided that the standardized value of PKAC is greater than 0.600

The first two rows of Table 5-5 show that when the standardized value of OSC use is greater than -0.938, the marginal return to MCC from an increase in PM is an increasing function of PKAC and vice versa; that is, the marginal return to MCC from an increase in PKAC is an increasing function of PM. Similarly, the third and fourth rows of Table 5-5 show that when the standardized value of PM is greater than -1.069, the marginal return to MCC from an increase in PKAC is an increasing function of OSC and vice versa; that is, the marginal return to MCC from an increase in OSC is an increasing function of PKAC. Finally, the fifth and sixth rows of Table 5-5 show that when the standardized value of PKAC is greater than 0.600, the marginal return to MCC from an increase in OSC use is an increasing function of PM and vice versa; that is, the marginal return to MCC from an increase in PM is an increasing function of OSC use.

These results not only are consistent with but also extend those derived from the interpretation of the sign and statistical significance of the standardized regression coefficients of the pairwise interaction terms in Model 4. As mentioned before, the positive and statistically significant regression coefficient for the interaction of PM and PKAC implies that PM and PKAC mutually amplify their positive effects on MCC when OSC use is at its mean value. In fact, Table 5-5 shows that this complementary effect manifests itself not only when OSC use is at its mean value but also when it is below that value, provided that it exceeds the threshold of -0.938.

Likewise, the positive and statistically significant regression coefficient for the interaction of OSC use and PKAC implies that OSC use and PKAC mutually amplify their positive effects on MCC when PM is at its mean value. In fact, Table 5-5 shows that this complementary effect manifests itself not only when PM is at its mean value but also when it is below that value, provided that it exceeds the threshold of -1.069.

Similarly, the non-significant regression coefficient for the interaction of OSC use and PM implies that OSC use and PM do not mutually amplify their positive effects on MCC when PKAC is at its mean value. In fact, Table 5-5 shows that this complementary effect manifests itself only when PKAC is 0.600 standard deviations above its mean value. From a theoretical point of view, this result underlines that PM and OSC use are complementary only at high values of PKAC. This result is consistent with those of Salvador et al. (2019), who found that the association between the use of an OSC and firm survival is positive only when market orientation (i.e., the ability to correctly interpret customer needs and infuse them into the product space) is high.

Table 5-6: Conditions for complementarities considering the movements of two variables simultaneously

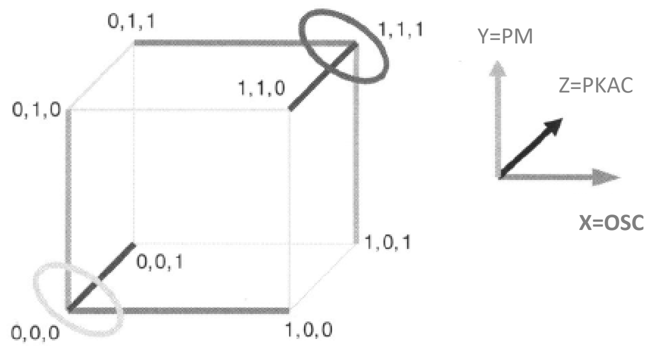
***X* = OSC** *Y* = PM *Z* = PKAC	$\beta_{xz} = 0.131$ $\beta_{xy} = -0.098$ $\beta_{xyz} = 0.143$	$G > -0.235$	The marginal return (in terms of MCC) from an increment in OSC use increases as PM and PKAC simultaneously rise, provided that their standardized values are both greater than -0.235
***X* = PM** *Y* = OSC *Z* = PKAC	$\beta_{xz} = 0.133$ $\beta_{xy} = -0.098$ $\beta_{xyz} = 0.143$	$G > -0.169$	The marginal return (in terms of MCC) from an increment in PM increases as OSC use and PKAC simultaneously rise, provided that their standardized values are both greater than -0.169
***X* = PKAC** *Y* = PM *Z* = OSC	$\beta_{xz} = 0.131$ $\beta_{xy} = 0.133$ $\beta_{xyz} = 0.143$	$G > -1.004$	The marginal return (in terms of MCC) from an increment in PKAC increases as PM and OSC use simultaneously rise, provided that their standardized values are both greater than -1.004

Regarding the conditions for complementarity when two variables are moved simultaneously, the first row of Table 5-6 shows that the marginal return to MCC from OSC use increases with PM and PKAC when the standardized values of PM and PKAC are both greater than -0.235. In turn, the second row shows that the marginal return to MCC from PM increases with OSC and PKAC when the standardized values of OSC and PKAC are both greater than -0.169. Finally, the last row of Table 5-6 shows that the marginal return to MCC from PKAC increases with OSC and PM when the standardized values of OSC and PM are greater than -1.004.

On the whole, the results reported in Tables 5-5 and 5-6 support the existence of complementarities between OSC use, PM, and PKAC.

5.2.2 The cube view of three-way complementarities

The cube view of three-way complementarities (cf. Section 4.1.2.2) implies that four tests should be performed to detect complementary effects of OSC use, PM, and PKAC on MCC (Figure 5-3). In order to perform such tests, the continuous variables measuring the three focal practices (i.e., OSC use, PM, and PKAC) are transformed into dichotomous variables by using the median value as the splitting criterion: values above the median are labeled with 1, while values below the median are labeled with 0. As explained in Section 4.1.2.2, the four complementarity tests can be viewed as comparisons among the edges of a cube, where each axis represents one of the dichotomized variables. Figure 5-3 shows a 1 x 1 x 1 cube, with the *x*-axis representing OSC use, the *y*-axis representing PM, and the *z*-axis representing PKAC. The binary version of the variable is used to label the coordinates in the cube. For example, the coordinate (1, 1, 1) indicates that a plant uses all three practices at a high level.



Four tests of complementarity:

OSC test	$MCC(A_{111}, Vc) - MCC(A_{011}, Vc) > MCC(A_{100}, Vc) - MCC(A_{000}, Vc)$
PM test	$MCC(A_{111}, Vc) - MCC(A_{101}, Vc) > MCC(A_{010}, Vc) - MCC(A_{000}, Vc)$
PKAC test	$MCC(A_{111}, Vc) - MCC(A_{110}, Vc) > MCC(A_{001}, Vc) - MCC(A_{000}, Vc)$
System test	$[MCC(A_{111}, Vc) - MCC(A_{011}, Vc)] + [MCC(A_{111}, Vc) - MCC(A_{101}, Vc)] +$ $[MCC(A_{111}, Vc) - MCC(A_{110}, Vc)] - [MCC(A_{100}, Vc) - MCC(A_{000}, Vc)] +$ $[MCC(A_{010}, Vc) - MCC(A_{000}, Vc)] + [MCC(A_{001}, Vc) - MCC(A_{000}, Vc)] > 0$

Figure 5-3: The cube view of complementarities and the associated four tests of complementarity (adapted from Tambe et al., 2012)

Each of the first three tests reported in Figure 5-3 considers MCC differences along a pair of edges, while the fourth test (i.e., the system test) simultaneously considers performance differences along all three pairs of edges. The symbol Vc in Figure 5-3 represents the vector of control variables.

The first test (labeled “OSC test”) determines whether introducing an OSC in the presence of PM and PKAC yields greater benefits, in terms of MCC increment, than introducing the same practice when PM and PKAC are absent; that is, whether

$K_{p\ OSC} = MCC(A_{111}, Vc) - MCC(A_{011}, Vc) - MCC(A_{100}, Vc) + MCC(A_{000}, Vc) > 0.$

Similarly, the second test (labeled “PM test”) determines whether implementing PM in the presence of OSC and PKAC yields greater benefits, in terms of MCC increment, than introducing the same practice when OSC and PKAC are absent.

Likewise, the third test (labeled “PKAC test”) determines whether plants that already have OSC and PM achieve greater MCC increments from the adoption of PKAC than plants that have neither OSC nor PM.

Finally, the fourth test (labeled “System test”) combines the previous three. Accordingly, this test assesses, for each of the three focal practices, whether the plants that implement the full system of putative complements (1, 1, 1) by adding just that practice (i.e., starting from the presence of the other two) experience a greater MCC improvement than plants that adopt the same practice but in isolation (i.e., starting from (0, 0, 0)).

The results of the four tests are presented in Table 5-7.

Table 5-7: Results of the four complementarity tests

Test	$\widehat{K}_p$	$SE(\widehat{K}_p)$	One-tailed *t*-test (right)	
			t	*p*-value
1) OSC	0.692	0.244	2.831	0.003
2) PM	0.168	0.263	0.639	0.262
3) PKAC	0.218	0.244	0.892	0.187
4) System	1.077	0.585	1.842	0.033

The result of the OSC test supports the view that plants gain greater benefits, in terms of MCC, from OSC use when they have already implemented PM and PKAC. In contrast, the PM test did not find support for the view that plants that already have both OSC and PKAC obtain greater MCC benefits from adopting PM than plants that have neither. Similarly, the PKAC test did not find support for the view that plants that already have both OSC and PM obtain greater MCC benefits from the adoption of PKAC than plants that have neither. However, and most importantly, the system test supported the existence of the three-way complementarities between OSC, PM and PKAC. As observed by Aral et al. (2012), the system test has greater statistical power than any of the three previous tests. In Aral et al.'s (2012: 927) words, the system test "assesses whether firms that complete the system of complements (1, 1, 1) by adopting just one of the three practices […] experience a greater productivity gain than firms that choose to adopt the same practice but in isolation (i.e., starting from (0, 0, 0) and adding one practice)." Therefore, the result of the system test clearly supports the existence of three-way complementarities between OSC use, PM, and PKAC.

5.3 Second-order latent-factor approach

Finally, the present thesis adopted Tanriverdi and Venkatraman's (2005) second-order latent-factor approach by modeling complementarities among OSC use, PM, and PKAC as a reflective second-order latent factor (complementarity model, depicted in Figure 5-4). A reflective second-order latent factor is, in this case, an unobservable factor that accounts for the multilateral interactions and covariance among OSC use, PM, and PKAC. Pragmatically, that means that the variances and covariances of the first-order factors (i.e. OSC use, PM and PKAC) are no longer estimated parameters in the model, but they are governed by the second-order latent factor (Segars et al., 1998). To assess the performance effects of a complementary system of practices, the performance effect of the second-order factor should be compared with the performance effects of the individual system components. Therefore, the second-order model is compared with a model that hypothesizes that OSC use, PM, and PKAC have independent effects on MCC (independent-effects model, depicted in Figure 5-5). The two models were compared using SEM with the IBM SPSS Amos v22 software package.

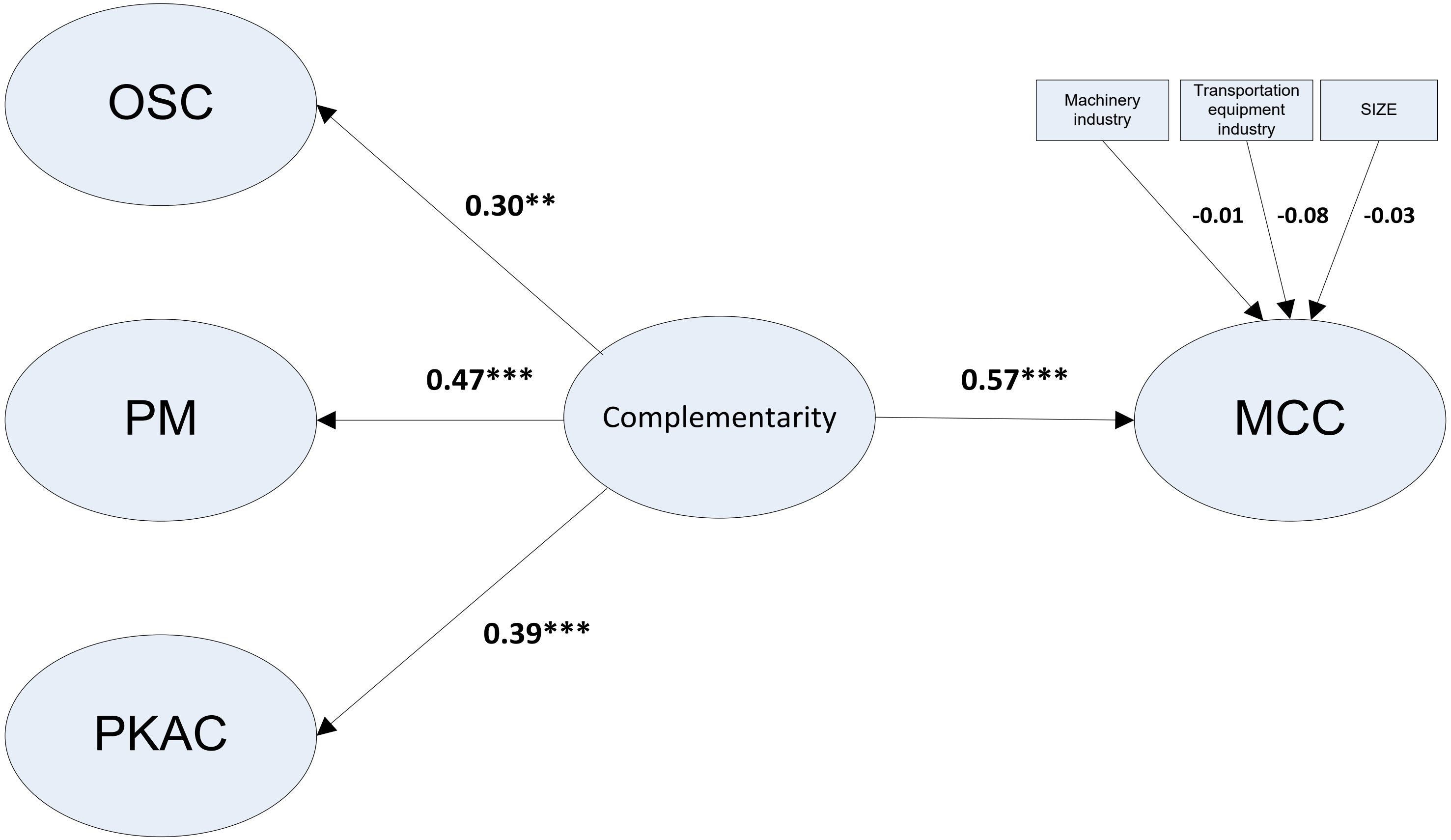


Figure 5-4: Complementary effects of OSC use, PM, and PKAC on MCC—structural model estimates (**p < 0.05; ***p < 0.01)

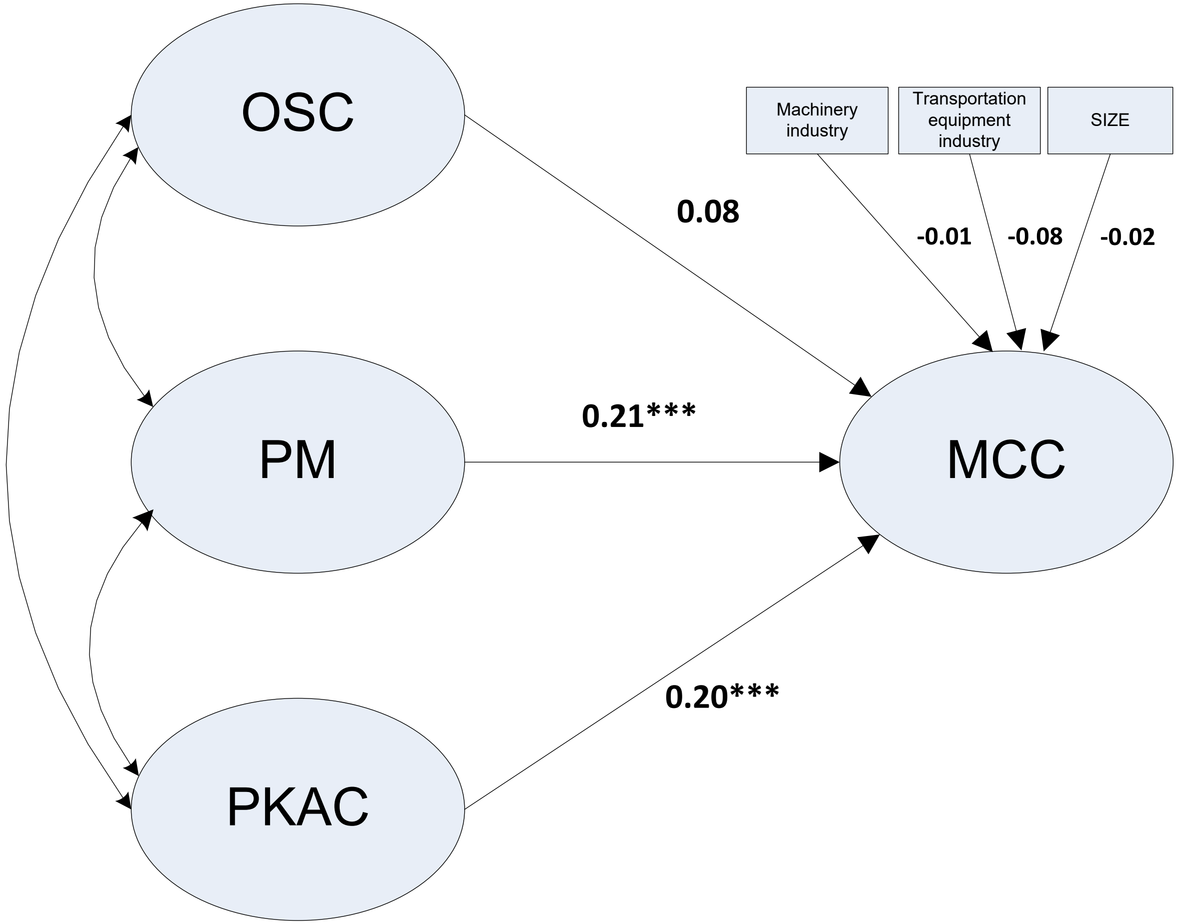


Figure 5-5: Independent effects of OSC use, PM, and PKAC on MCC—structural model estimates (***p < 0.01)

Acceptance of the complementarity model over the independent-effects model was supported by the following criteria:

- First, the comparison of the goodness of fit statistics for the two models (Venkatraman, 1990). The typical fit indices are almost identical for both models (complementarity model: $\chi 2$ (df) = 224.71 (115), $\chi 2$/df = 1.95; TLI = 0.88, CFI = 0.9, IFI = 0.9, RMSEA = 0.067 (0.054–0.08); independent-effects model: $\chi 2$ (df) = 223.76 (113), $\chi 2$/df = 1.98; TLI = 0.88, CFI = 0.9, IFI = 0.9, RMSEA = 0.068 (0.055–0.081)), but the second-order model is more parsimonious and, therefore, should be preferred (Venkatraman, 1990).

- Second, the value of the target coefficient (*T*) statistics (Marsh and Hocevar, 1985). The target coefficient is the ratio of $\chi 2$ values of first- and second-order models and has an upper limit of 1. In this case, the *T* value is 0.99, which implies that the complementarity model accounts for 99% of the relations among the first-order factors in the independent-effects model and, thus, effectively explains the covariation among the first-order factors.

- Third, the significance levels of the factor loadings of the second-order construct (Venkatraman, 1990; Tippins and Sohi, 2003). Figure 5-4 shows that all the factor loadings of the second-order construct capturing the complementarity of the three practices are positive and highly significant.

- Fourth, the significance levels of the structural paths that link the second-order factor to a criterion variable of interest (Venkatraman 1990). Figure 5-4 shows that the second-order factor capturing the complementarity of the three practices has a very strong, positive, and highly significant impact on MCC.

- Finally, the comparison of the values of the squared multiple correlations (SMC) for MCC in the two models. The SMC value is the equivalent of R^2 in regression analysis, as it indicates what percentage of the variance of the outcome variable is explained by its predictors in the model. The SMC value for MCC in the complementarity model (SMC = 33%) is much greater than in the independent-effects model (SMC = 12%). This implies that the complementarity model explains much more variance in MCC than does the independent-effects model.

Collectively, these results support acceptance of the complementarity model over the independent-effects model. In turn, the acceptance of the complementarity model provides support for the hypothesis that using OSC, PM, and PKAC in concert has positive interaction effects on MCC.

5.4 Overview of the results

To summarize, altogether the results of the three different approaches (i.e., adoption, performance equation, and second-order latent-factor approaches) provide support for the research hypothesis that OSC use, PM, and PKAC have a positive complementary effect on MCC.

As observed in Section 5.1.1, the results of the adoption approach should be seen as preliminary evidence regarding whether managers perceive the practices of OSC use, PM, and PKAC as mutually beneficial, rather than as evidence for the existence or nonexistence of complementarities. The results of this approach suggest that PM drives the adoption of PKAC only when OSC use is also adopted and, likewise, that PKAC drives the adoption of OSC use only when PM is adopted as well. While these findings support the hypothesis of three-way complementarities among OSC use, PM, and PKAC by suggesting that the three practices are more likely to be adopted jointly than separately, the pairwise correlations between OSC use and PM are never statistically significant, not even in the case of high PKAC. It must be recalled, however, that a positive correlation between practices is neither necessary nor sufficient evidence of complementarities among the same practices (Arora 1996; Athey and Stern, 1998).

Along the same line, the performance equation approach, in its two different applications (i.e., the productivity test and the four tests associated with the cube view of complementarity), supports the importance of using the system of complements as a whole. The results of this approach suggest that any subset of the system (i.e., two of the three practices, without the third) forgoes the full potential benefits, in terms of MCC, that derive from the joint implementation of OSC use, PM, and PKAC.

Finally, the second-order latent-factor approach provides additional evidence in support of the research hypothesis. This is because the second-order factor capturing the complementarity of OSC use, PM, and PKAC has a very strong, positive, and highly significant impact on MCC and because this second-order model explains much more variance in MCC than does the model assuming that OSC use, PM, and PKAC have independent, instead of synergistic, effects on MCC.

6. Discussion and conclusions

6.1 Theoretical contribution

Up to now, the mass-customization literature has recognized the important role of OSCs in MCC development (Franke and Piller, 2003; Heiskala et al., 2007; Forza and Salvador, 2008), but large-scale empirical studies focused on the impact of OSC use on MCC are still missing. The present research starts to narrow this gap by conceptually and empirically examining not only the main effect of OSC use on MCC but also the impact of the interplay of OSC use and two other MCC enablers that prior research has related to OSCs and to OSC effectiveness in improving MCC. In its initial, conceptual part, the present dissertation develops a logical explanation for the hypothesis that there exist three-way complementarities between OSC use, PM, and PKAC, as far as MCC development is concerned. In its second, empirical part, the hypothesis is tested using survey data from a sample of mid- to large-sized manufacturing plants in 3 industries and 15 countries around the globe. In this last part, the theoretical and practical contributions of the dissertation are discussed and, finally, its limitations, along with the related opportunities for further research, are outlined.

A major contribution of the hypothesis development part of the thesis lies in the integration and organization of various suggestions and results scattered in the existing literature according to two types of mechanisms of complementarity and, secondly, in the provision of detailed, logical explanations for the working of these mechanisms with regard to the three putative complements of interest to this study. Briefly, the first type of complementarity mechanism consists of the mutual reduction of implementation costs, and the thesis argues that the three practices of OSC use, PM, and PKAC reciprocally reduce the costs of their implementation. The second mechanism is the mutual amplification of MCC benefits, and the thesis maintains that these same three practices mutually increase their benefits in terms of MCC. It is important to recall that cost reduction plays an important role in the development of MCC and, therefore, the mutual reduction of implementation costs has, ultimately, a positive impact on MCC.

The empirical part of the dissertation has tested the hypothesized three-way complementarities using three different approaches developed in the relevant literature: the adoption approach, which uses multiple regression analysis to examine whether or not the putative complements are positively correlated, conditional on other observable characteristics (e.g., Arora 1996; Aral et al., 2012; Bryjolfsson and Milgrom, 2012); the performance equations approach, which uses multiple regression analysis to examine whether or not the performance outcome of adopting the hypothesized complements together is greater than the sum of the performance outcomes of adopting each complement separately (e.g., Arora 1996; Aral et al., 2012; Bryjolfsson and Milgrom, 2012); and, finally, the second-order latent-factor approach, which uses SEM to compare the performance effects of the individual, putative complements with the performance effects of the full system of complements (e.g., Tanriverdi and Venkatraman, 2005). Notably, while the combination of the adoption approach with the performance equation approach has already been proposed and carried out in previous studies on complementarities (e.g., Cassiman and Veugelers, 2006; Aral et al., 2012; Tambe et al., 2012), the triangulation of these two approaches with the second-order latent-factor approach developed by Tanriverdi and Venkatraman (2005) represents a contribution of the present work to the study of complementarities. This contribution was inspired by Tambe et al.'s (2012: p. 849) observation that the empirical strategy followed by prior research to test for complementarities between organizational practices is "to marshal a number of different types of evidence consistent with the complementarities hypothesis, which, when considered in whole, strongly suggest complementarities between organizational practices." In the case of the present research as well, almost all the results obtained from the application of the different approaches converge in supporting the hypothesized three-way complementarities between OSC use, PM, and PKAC. The only conflicting result is represented by the pairwise correlations between OSC use and PM that were computed according to the adoption approach (cf. Table 5 3). However, this result may be explained by the inherent limitation of the adoption approach in detecting complementarity effects (Aral et al., 2012). This approach does not asses the productivity premium derived from the adoption of a set of complementary practices, but it only assesses if a set of practices tend to be adopted together (Aral et al., 2012). Therefore, the results obtained with this approach inevitably depend on how much managers are aware of the benefits that their company could reap from the joint implementation of the set of practices (Aral et al., 2012).

This finding enriches the MCC literature by improving the understanding of how, why, and under what conditions the use of an OSC influences a manufacturing organization's MCC. However, at least two other contributions can be envisaged.

First, the results add to the debate on the interrelationships between MCC enablers, which is still in its infancy. Prior research has typically analyzed the individual effects of different enablers on MCC (e.g., Tu et al., 2004; Liu et al., 2006) and only recently, two studies have begun to shed light on how the interrelationships between different MCC enablers impact MCC: Zhang et al. (2015b) and Salvador et al. (2015). None of these studies, however, has focused on the interplay among the three MCC enablers of interest in the present research.

Secondly, this finding provides indirect support for the reasoning of Salvador et al. (2009), widely accepted in the mass-customization literature, that mass customization requires three fundamental capabilities: solution space development, robust process design, and choice navigation. Notably, an organization's ability to identify the product attributes along which customer needs diverge, which Salvador et al. (2009) termed solution space development, is supported by PKAC (Kristal et al., 2010; Zhang et al., 2015a). In turn, PM is an important concept behind robust process design (ElMaraghy et al., 2013; Bossen et al., 2017), that is, the ability to reuse or recombine existing organizational and value-chain resources to fulfill a stream of differentiated customer needs (Salvador et al., 2009). Finally, an OSC is a tool that can enable choice navigation (ElMaraghy et al., 2013; Tiihonen et al., 2013), defined by Salvador et al. (2009) as the capability to support customers in identifying their own solutions while minimizing complexity and the burden of choice. Therefore, the empirical support found by the present thesis for the existence of three-way complementarities between OSC use, PM, and PKAC indirectly supports Salvador et al.'s (2009) conceptual argument that a company requires all three capabilities of solution space development, robust process design, and choice navigation to mass-customize its offerings.

6.2 Practical contribution

The present research provides some useful insights for practitioners. The results of this study make firms pursuing mass customization aware of the fact that investing in an OSC without also investing in PM and PKAC is not likely to improve MCC. Conversely, balanced investments in all three of these practices will yield higher MCC than investing in either any one or any pairs of them alone.

Nowadays, e-commerce is increasingly becoming a necessity for companies, which otherwise could be left behind by the competition. This trend also involves companies pursuing mass customization. These firms have the possibility to use a potentially powerful tool for supporting online shopping, that is, an OSC, which recent technological advancements promise to make even more appealing through connections with social software (e.g., Grosso et al., 2017), computer-aided design (CAD) systems, (e.g., Tiihonen et al., 2013), and augmented or virtual reality applications (e.g., Luh et al., 2013).

Companies that, allured by these promises, plan to invest in OSC development/implementation should not forget to also invest in the enhancement of PM and PKAC. Investment in PM and PKAC, along with investment in advanced OSCs, appears to be fundamental to more fully realizing the potential benefits, in terms of MCC, of these innovative technologies.

6.3 Limitations and future research directions

As with any other piece of research, this study is not without limitations, which could be addressed in future research. The dataset used in this study includes only three industries. Given that more and more companies in a variety of sectors use OSCs to offer their products on the Internet (e.g., Walcher and Piller, 2012; Abbasi et al., 2013; Blazek et al., 2016), a future research opportunity is to include other industries in the study.

In addition, the effect of the customer position in the supply chain (e.g., industrial customers vs consumers) might be a relevant control variable in this study. However, I decided not to include it due to the large number of missing data for the two items measuring the percentage of plant sales in each of the two categories: “business-to-business” and “business-to-commerce”.

Another limitation is related to the cross-sectional nature of the used dataset, which limits the ability to explore causal links. Therefore, a research opportunity is to examine the relationships of interest in this study using a longitudinal research design.

Finally, even though MCC is an important construct that captures the ability of an organization to provide product customization without considerable trade-offs in cost, delivery, and quality performance, an additional future research direction, in accord with Salvador et al.’s (2019) suggestion, is to use other outcome variables, such as objective performance measures.

7. References

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