AMBIDEXTERITY 4.0: HOW ADOPTING SMART MANUFACTURING TECHNOLOGIES IMPROVES BOTH EXPLOITATION AND EXPLORATION

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ABSTRACT

"Industry 4.0" aims to increase competitiveness and it is generally fostered by increasing efficiency within operational processes. Nevertheless, sustainable competitive advantage depends on a company's ability to exploit its current assets while simultaneously exploring new ways of producing value, i.e. being ambidextrous. In this paper we wonder whether investments in Smart Manufacturing Technologies (SMTs) allow companies to be ambidextrous as it represents a gap in the literature. A quantitative method has been used to answer, leveraging on data coming from the 3rd CINet Survey involving hundreds of companies worldwide. A model made of constructs and relationships is introduced where we find: business performances, investment in SMTs, ambidexterity and innovation performance. The model has been tested through structural equation modelling (SEM) and several interesting conclusions are stemming from the statistical analysis. First, the adoption of SMT positively affects the capability of simultaneously pursuing exploitation and exploration strategies within different departments, thus fostering structural ambidexterity. Secondly, results show that pursuing structural ambidexterity, companies can increase their innovation performance, thus filling another literature gap. Moreover, the research shows that companies with good business performances are in a favourable position to invest in SMTs and consequently to increase their innovation performance. Our results shed a novel light on the current debate over industry 4.0 transition, with implications also for practitioners and manufacturing companies, as payback for expensive investments in SMT should be searched not only in improved short-term business performances, but also in better long-term innovation performances.

1.INTRODUCTION

Nowadays companies are facing a complex, highly competitive and rapidly changing environment, characterized by the presence of continuous technological innovation. The transition toward "Industry 4.0" is generally fostered by envisaging productivity gains, better control over operations and supply chain processes and, therefore, improved competitiveness. These factors are indeed relevant to achieve success, but sustainable competitive advantage depends on a company's ability to exploit its current assets while simultaneously exploring new ways of producing value or, in other terms, they need to be ambidextrous (Bodwell and Chermack 2010).

The literature has deeply investigated how to overcome the trade-off between exploitation and exploration, distinguishing reconciling actions at intra- and inter-organizational levels (Petruzzelli, 2019). Recently researchers have started focusing on the pivotal role that digital technologies may have in this process (Gastaldi et al., 2018; Park et al., 2020) and, in this scenario, manufacturing stands out as an interesting field, due to the increasing role of digital technologies.

In this paper we investigate the expectation that Industry 4.0 may have strong connection with ambidexterity: by digitally interconnecting process flows with products during the manufacturing process and their lifecycle, manufacturing organizations would be able to achieve remarkable results both in the short-term and in the long-term. This expectation has been checked through a literature review, which investigated both ambidexterity and industry 4.0 and, out of the literature review, a main research question arises: do investments in Smart Manufacturing Technologies (SMTs) allow companies to be ambidextrous, and thus to pursue at the same time exploitation and exploration?

To provide a quantitative answer to this question, we used data coming from the 3rd CINet Survey, administered from November 2016 to June 2017 and involving over 370 companies worldwide; constructs and relationships amongst business performances, investment in SMT, ambidexterity and innovation performances are defined and investigated, together with the impact of several control variables.

Providing an evidence for such a relationship may represent a key contribution, helping manufacturing companies in finding a better balance when justifying the investments required in their digitization programs. If ambidexterity is proven, in fact, the investment payback should be searched not only in improved short-term business performance but also in better long-term innovation performance.

2.THEORETICAL BACKGROUND

1.1. Ambidexterity

The term “ambidexterity” was first introduced by (Duncan 1976). However, the scientific debate around it started in 1991, when March proposed the constructs “exploitation” and “exploration” to identify the two divergent strategies constituting ambidexterity. On one hand, exploitation means leveraging on existing resources and is about consolidating, refining, becoming more efficient in the utilization of existing resources (e.g., equipment, knowledge). On the other one, exploration represents the way companies search for new opportunities and get out of their “comfort zone” pursuing variation, risk taking, experimenting, innovating products or processes (March 1991).

The right balance between exploration and exploitation is difficult to be achieved and maintained (Levinthal and March 1993). Currently, there is somewhat a consensus about the merits of this balancing process (Lavie, Stettner, and Tushman 2010); however, there is little agreement on the means by which organisations pursue such balance (Adler et al. 2009). As a matter of fact, only by focusing on intra-firm balancing processes, literature is divided between two approaches (Eisenhardt, Furr, and Bingham 2010; Schreyögg and Sydow 2010), which differ in terms of their emphases on differentiation rather than integration when tackling the diverging alternatives (Andriopoulos and Lewis 2009).

On one side there are the structural approaches to ambidexterity, which stress the usage of structure and strategy to enable differentiation among organisational units. Segregated efforts target either one or the other dichotomous activities (Andriopoulos and Lewis 2009). On the other side there are the contextual approaches to ambidexterity, which—mostly rooted in organisational learning and innovation management literature streams—utilise behavioural, cognitive and social means to integrate the diverging activities (Gibson and Birkinshaw 2004; Eisenhardt, Furr, and Bingham 2010). Recently scholars have developed hybrid models, which combine aspects coming from both structural and contextual ambidexterity models (Ossenbrink, Hoppmann, and Hoffmann 2019).

Once outlined the concept of ambidexterity, it is important to give an overview regarding how it is measured in literature. Cao et al. (2009) discuss the two fundamental concepts beyond measurement models: “combined dimension” and “balance dimension”.

Nevertheless, there is no consensus regarding which method should be used, as ambidexterity could be measured in different ways. Given any measure of the two constructs exploration and exploitation, any operator that could be used to obtain a score for ambidexterity shows strengths and weaknesses. For instance, the sum operator – i.e. “combined dimension” – is the simplest way to assess ambidexterity and provides the lowest loss of significance with respect to the other models (Lubatkin et al. 2006) but it neglects the perspective of “balance dimension”, as a company which scores 1 and 6 in the two dimensions appears to be more ambidextrous than one scoring 3 and 3, while in reality the focus should be on combined action of the two capabilities. The multiplication operator (Gibson and Birkinshaw 2004) captures the interaction effect but it suffers from multicollinearity; moreover, with the multiplication, a company which scores 2 and 3 in the two dimensions appears to be more ambidextrous than one scoring 2 and 2 and this is – again - partially in contrast with the idea of “balance dimension”. Finally, the “absolute value of the subtraction” operator seems to be the most accurate with regard to the balance, but again a company which scores 1 in both dimensions appears to be equally ambidextrous as one scoring 5 and 5, and this is absurd. With regards to the latter, Simsek (2009) states that an organization with low levels of exploitation and exploration is balanced but not ambidextrous.

2.2. Industry 4.0 and SMTs

Around 2010 academics and practitioners observed an upcoming transformation in the manufacturing sector, due to changes in customers’ behaviour and to the maturation of new promising technologies (Brousell, Moad, and Tate 2014). This phenomenon has been defined as the Fourth Industrial Revolution, which has led to the definition of “Industry 4.0” (term coined in Germany), or sometimes defined as “Smart Manufacturing” (firstly conceptualised in USA).

Industry 4.0 can be defined as “a vision of the future of industry and manufacturing in which digital technologies boost efficiency and competitiveness by interconnecting every resource (data, people and machinery) in the Value Chain” (Miragliotta et al. 2018).

Although there is not consensus about which technologies belong to the Industry 4.0 paradigm, a remarkable number of papers – e.g. Miragliotta and Shrouf (2013) and Frank et al. (2019)– states that internet of things, big data analytics and cloud manufacturing represent its core. Other scholars, such as Culot et al. (2020), enlarge the scope to other operational technologies such as additive manufacturing (also known as 3D printing), advanced human-machine interface and advanced automation (e.g. collaborative robot).

We refer to them as Smart Manufacturing Technologies (SMTs), which can be clustered in two groups (Tedaldi and Miragliotta 2020):

- Information Technology (IT): encompassing internet of things, data analytics and cloud manufacturing;
- Operational Technology (OT): encompassing advanced human-machine interface, advanced automation and additive manufacturing.

SMTs, in integration with existing traditional IT systems – as enterprise resource planning, computer aided process planning and product data management / product lifecycle management — and OT automation systems — as programmable logic controllers and supervisory, control and data acquisition systems — are the fundamentals of today's digital manufacturing (Lu 2017).

Recently academics compared Industry 4.0 with other major trends, such as sustainability and servitization. de Sousa Jabbour et al. (2018) propose a framework including eleven critical success factors enterprises should manage when integrating Industry 4.0 and "green" (i.e., environmental-sustainable) manufacturing. Frank et al. (2019b) discuss the link between Industry 4.0 and servitization and propose a conceptual framework where the latter can lead to the creation of "manual", "digital" and "Industry 4.0" services for customers where digital technologies can open new channels of data and information gathering, aiming to foster a business feedback that enables improvements within the processes of the manufacturing companies.

Today it's universally acknowledged that SMTs help companies in increasing efficiency (Xu and Duan 2019). However, some authors state that they can be enablers for innovation as well. For instance, (Bressanelli et al. 2018) explore the role of internet of things, big data and analytics as enabling factors for the introduction of new business models; they identify some functionalities enabled by such technologies that deals with the circular economy paradigm, in which the capability of a company of innovating its products is central.

2.3. Gaps and objectives of the study

The review of extant literature has shown an almost complete absence of research that simultaneously considers SMTs adoption and ambidexterity in intra-organizational contexts. Halse and Ullern (2017) claim that – for a manufacturing company – both openness to an external network of partners and organizational ambidexterity are vital for its "Industry 4.0 transformation". Szalavetz (2019) investigates the impacts of advanced manufacturing technologies belonging to the Industry 4.0 paradigm on the subsidiaries of an enterprise, and so beyond the intra-organizational level. In spite of papers evaluating the antecedents or the outcomes of both ambidexterity in the Industry 4.0 era, to the best of authors' knowledge no paper investigated SMTs effects on firms' ambidextrous strategy. Gastaldi et al. (2018) analyse how digital technologies can help healthcare organizations in improving the exploration-exploitation paradox over time. However, their study is confined in healthcare organizations, excluding manufacturing.

As regard to Industry 4.0, many authors studying the topic are focusing their attention on the benefits of SMTs adoption and how SMTs can have an impact over business performance of a company (Gastaldi et al. 2015; Jeschke et al. 2017; Dalenogare et al. 2018). Nevertheless, as suggested by Piening and Salge (2015), there are not works investigating the opposite relationship, i.e. studies which assess business performances as enablers for SMTs adoption, and conducive to innovation performance. This gap should be covered since many SMTs applications require high investments and companies with good business performance could be in favourable positions for the implementation.

As regards to ambidexterity, many scholars concentrate on the consequences of this capability, e.g. investigating innovation performance without defining how companies should behave to put in practice exploitation and exploration simultaneously. He and Wong (2004) recognize that their study does not address the issue of which organizational design principle are appropriate for ambidexterity. Some scholars have argued that, if a company wants to excel in both improving existing products and generating new ones, it should apply structural ambidexterity (Raisch and Birkinshaw 2008; Levinthal and March 1993; Gibson and Birkinshaw 2004); anyway, no one has clearly demonstrated that structural ambidexterity could have a positive influence on innovation performance.
Considering the outlined literature gaps, three specific research questions (RQs) arise:

- RQ1: Do SMTs allow company to be ambidextrous and thus simultaneously pursue exploitative and explorative strategies?
- RQ2: Are well performing companies in a good position to implement SMTs?
- RQ3: Do exploitation, exploration and structural ambidexterity have a positive impact on innovation performance?

3. HYPOTHESIS AND MODEL

To properly answer to the outlined RQs, the conducted work relies on a model which incorporates six hypotheses, as depicted in Figure 1.

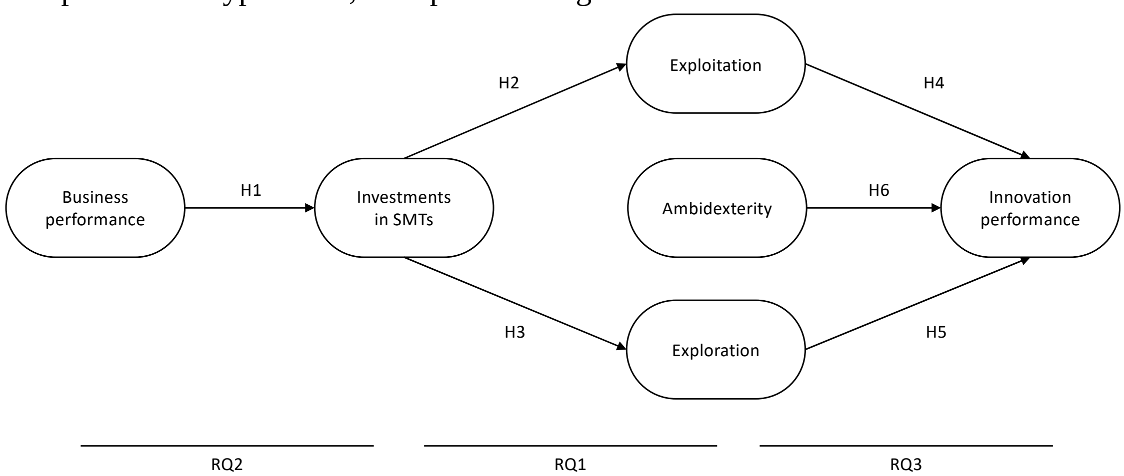

Figure 1. Research questions and hypotheses

The first hypothesis is to understand whether good business performance foster the adoption of SMTs. The belief to be proved is that companies able to achieve good business performance are well positioned to carry out investments (Sharfman et al. 1988) and this could be an important factor for SMTs adoption which can be very costly (Lin and Chen 2012) as it usually requires ad-hoc designed solution for a specific company (Müller, Kiel, and Voigt 2018). Relying on these arguments, we define the first hypothesis as H1:

H1. Good business performance of a company positively influences its implementation of SMTs.

The second hypothesis supposes a positive relation of SMTs on exploitation. It comes from the idea that, during the last decades, several authors studied digital technologies as one of antecedents of exploitation (Stein and Zwass 1995; Xue, Ray, and Sambamurthy 2012; Malhotra 2001). Moreover, the initial objectives of companies which undertake a digital transformation initiative is generally that of exploiting more effectively their resources and achieve higher efficiency in term of time saving, cost reduction or managerial simplification (Gastaldi et al. 2018). Regarding the SMTs, (Ali and Azad 2013) consider their benefits from the operational perspective, and highlight the optimization of the time-cost trade-off, increased energy savings, and Kang et al. generally talk about increased efficiency. Thus, H2 can be defined as:

H2. The adoption of SMTs has a positive influence on exploitation within a company.

The third hypothesis comes from the evidence that, once companies can reach the main benefits of initial digitisation investments, the introduced digitisation system allows the exploration of new and radical ways of providing products or services (Gastaldi et al. 2018). Digital technologies are expected to improve data collection and processing, thus allowing organization to respond to market changes in timely manner and identify new business opportunities (Chaudhuri, Dayal, and Narasayya 2011). Basing on these arguments, the next hypothesis follows:

H3. The adoption of SMTs has a positive influence on exploration within a company.

As regard to the fourth one, it's acknowledged that exploitation enhance short-term performance (Atuahene-Gima 2005) but at the same time some authors reveal positive influence on both short-term and long-term innovation performance (i.e. continuous improvement and radical innovation) (He and Wong 2004). Firms following an exploitation strategy for their operations should benefit in innovation performance, due to more suitable processes (Benner and Tushman 2002; Lee, Lee, and Garrett 2019). Atuahene-Gima and Murray (2007) suggest that companies increasing their exploitation capabilities will become more efficient in their learning processes and this positively influence their innovation performance. On the basis of these ideas, H4 follows:

H4. The level of exploitation within a company has a positive influence on its overall innovation performance.

The fifth hypothesis aims at studying the relationship between the exploration level of a company and its overall innovation performance. Atuahene-Gima and Murray (2007) and He and Wong (2004) discover same results found for exploitation vs innovation performance. Nerkar (2003) demonstrated that the higher the exploration, the greater is the impact on knowledge creation but he discovers also that for high level of exploration returns could decrease, thus showing an inverted U-shape relationship and this is somehow recognized also by Li et al. (2010). Indeed, H5 reflects these arguments and follows:

H5. The level of exploration within a company has a positive influence on its overall innovation performance.

In this study, the examined ambidexterity is the structural one, which sees the operations and the innovation departments of an enterprise as separated: the former should be oriented to exploitation, while the latter on exploration. The last hypothesis roots on the idea that, by balancing exploitation and exploration activities, the overall innovation performance should improve. Many authors agree with this idea, for instance Katila and Ahuja (2002) and Nerkar (2003) suggest that firms enhance their innovation performance from pursuing both exploitation and exploration. Conversely, other authors, such as Atuahene-Gima (2005), show ambidexterity has a negative influence on innovation performance and argue it is more suitable to couple high (low) exploitation with low (high) exploration, as a high-high couple could lead to tensions due to divergent nature of the two processes. However, we suppose a positive influence of structural ambidexterity on innovation performance as most of the authors, therefore:

H6. The structural ambidexterity of a firm has a positive influence on its overall innovation performance.

4. METHODS

4.1 Context and data

The research model was tested using data collected through the 3rd survey, a global research project carried out within the *Continuous Innovation Network* (CINet, more info at: www.continuous-innovation.net) through a common questionnaire administered simultaneously in 11 countries by local research groups from November 2016 to June 2017.

The sample frame used by each country was restricted to employees whose job titles included chief operating officers or chief technology officers. The survey focused on respondents from manufacturing firms indexed in the International Standard Industrial Classification (ISIC) codes ranging from 10 to 32. Several manufacturing firms were contacted to participate in the survey. After consent for research participation, survey questionnaires were distributed; a total of 138 usable survey responses were used to test the research hypotheses.

All country samples were checked for early and late response bias and non-response bias before being compiled in the global database. For early and late response bias tests, each country coordinator was required to compare the responses from the early respondents and late respondents (Armstrong and Overton 1977). A t-test of difference was carried out for sales figures, number of employees and ISIC code for early and late respondents without finding any statistically significant difference. For non-response bias test, each country coordinator compared the responses of respondents who returned the survey to those who did not answer the survey. A t-test of difference was performed for sales figures, number of employees and ISIC code. No statistical difference was found between the responses of respondents and non-respondents.

4.2 Measures

The measures adopted in the research are described below. Table 1 gives the complete list of items and information on the values of Cronbach's alpha of the various constructs.

Innovation performance. A 4-item scale ($\alpha = 0.76$) was developed. Following Prajogo and Ahmed (2006), we considered a broad definition of innovation performance, which consider aspects related to new product development (Atuahene-Gima 2005), employee skills (Pullman, Maloni, and Carter 2009), project planning accuracy (Griffin and Page 1993) and the capacity of launching environmental-friendly products (Wong, Turner, and Stoneman 1996). For each of these dimensions, we asked respondents to reflect on their average performance over the past three year, and to relate it to their main competitors. This would reduce the potential biases associated to idiosyncratic events.

Exploitation. four-item scale ($\alpha = 0.83$) was adapted from Atuahene-Gima (2005). All measures were assessed asking participants to focus on their operation through questions on a five-point Likert-type scale ranging from "strongly disagree" to "strongly agree". Table 1 reports the specific measures.

Exploration. A four-item scale ($\alpha = 0.73$) was adapter from Akman and Yilmaz (2008). All measures were assessed asking participants to focus on their innovation department through questions on a five-point Likert-type scale ranging from "strongly disagree" to "strongly agree". Table 1 reports the specific measures.

Ambidexterity. As illustrated in the literature review, the interaction between exploration and exploitation has been computed in the past according to different perspectives, without finding a consensus. In order to overcome this issue, we propose an alternative way of operationalizing ambidexterity, which simultaneously considers the combined and balance dimensions:

$$Ambidexterity = \frac{Combined\ dimension}{Balance\ dimension} = \frac{Exploitation + Exploration}{|\ Exploitation - Exploration\ |} \tag{1}$$

In case the value of the denominator becomes zero for any of the observations, the following formulas can be used instead:

$Ambidexterity = \frac{Exploitation + Exploration}{|\ Exploitation - Exploration\ | + 1}$ or alternatively,

$Ambidexterity = Min(\frac{Exploitation + Exploration}{|\ Exploitation - Exploration\ |}, \mathrm{M}_A)$,

where M_A is the maximum ambidexterity value within the observations that have a non-zero denominator.

This computation sums the magnitude of the two approaches and divide it by the relative imbalance between the two strategies. As a consequence, it simultaneously addresses two different perspectives: on the one hand, the numerator is the sum between exploitation and exploration, which reflects a way to calculate ambidexterity according to the combined dimension vision (Cao, Gedajlovic, and Zhang 2009); on the other hand, the denominator includes the absolute difference between exploitation and exploration, which is perfectly in line with the balance dimension theory (Cao, Gedajlovic, and Zhang 2009). Therefore, we overcome the main drawbacks related to sum or multiplication – i.e. difficulties in detecting the level of balance between the two strategies – and to absolute difference – i.e. enterprises scoring low in both approaches considered ambidextrous.

Investments in SMTs. A five–items scale ($\alpha = 0.74$) was adapter from Vázquez-Bustelo et al. (2007) and Bottani (2010), asking how much SMT were adopted and exploited within the respondent's company. All measures were assessed through participants responses to questions on a five-point Likert-type scale ranging from "not applied" to "high degree of application." Table 1 reports the specific measures.

Business performance. Business performance was measured as accomplished by McDougall and Tyers (1994) through three items that asked to assess on a five-point Likert scale (from "much lower" to "much higher") the average performance of the respondent's firm – in terms of net profit, return on sales and profit growth – relative to the main competitors over the past three years. Focusing on net profit, return on sales and profit growth ensures comprehensiveness in assessing business performance.

Control variables. We controlled for three variables: region, industry and company size. Region variable is incorporated with a set of dummy variables for South America, North America, Europe and Asia (which was considered as the reference category). Company size was measured through the number of employees. We stratified the companies in three groups: small companies with less than 50 employees, medium companies with 50 to 250 companies and big companies with more than 250 employees. Industry was coded as eight dummy variables corresponding to the industries of the various respondents (1 = Manufacturing of food products; 2 = Manufacturing of rubber and plastic products; 3 = Manufacturing of fabricated metal products (except machinery and equipment); 4 = Manufacturing of computer, electronic and optical products; 5= Manufacturing of electrical equipment; 6 = Manufacture of machinery and equipment; 7= Manufacturing of furniture; 8 = Others).

4.3 Data analysis

In order to answer our research questions, we performed a three-step methodology. First, we run exploratory factor analysis to identify the underlying constructs. Next, we conducted confirmatory factor analysis to test the distinctiveness of the constructs. Finally, Structural Equation Modelling (SEM) was used to test the hypotheses and reveal the relationships between various constructs. All the analyses were performed in Stata 14.

As for data pre-processing, we first checked the responses to make sure that there were no outliers. Then, the observations that had more than 4 missing values (out of the 23 relevant questions) were omitted from the analysis. Finally, we performed mean imputation for the remaining missing values. The final sample size after the data pre-processing is 138 answers.

Next, we performed Principal Component Analysis (PCA) and, in order to choose the appropriate number of factors, we accomplished a parallel analysis (with 1,000 repetitions), which is more accurate than considering the number of eigenvalues greater than one (Kaiser-Guttman criterion) or the scree plot (Hayton, Allen, and Scarpello 2004). Next, we assigned the items to the constructs according to the rotated factor loadings. We considered factor loadings that had an absolute value higher than 0.4. Cronbach’s alphas of the retrieved factors were calculated to assess their level of internal consistency. Following Kim et al. (2016), Cronbach’s alphas greater than 0.7 were considered acceptable. To test the sampling adequacy, we calculated the Kaiser-Meyer-Olkin (KMO) measure (Cerny and Kaiser 1977) and verified that it was higher than 0.5 (Hair et al. 2006).

As mentioned, SEM was used to examine the hypothesized model. In this study, we adopted Anderson and Gerbing's (1988) comprehensive, two-step analytical strategy to test the hypothesized model depicted in Figure 1. In addition, we also report the Comparative Fix Index (CFI; Bentler, 1990), the Standardized Root Mean Square Residual (SRMR), and the Root Mean Square Error of Approximation (RMSEA; Steiger, 1990) to gauge model fit. The CFI has been considered the best approximation of the population value for a single model, with values greater than or equal to 0.90 considered indicative of good fit (Medsker, Williams, and Holahan 1994). The SRMR is a standardized summary of the average covariance residuals. A favorable value is less than 0.10 (Kline 1998). The RMSEA is a measure of the average standardized residual per degree of freedom. A favorable value is less than or equal to 0.08, and values less than or equal to 0.10 are considered “fair” (Browne and Cudeck 1989).

5. RESULTS

5.1 Exploratory factor analysis

Although all measures have been already tested in the literature, we performed exploratory factor analysis including all 22 items corresponding to the 5 measures (business performances, SMTs, exploitation, exploration, innovation performance). This provides further evidence on the discriminant validity of the measures.

As mentioned, we used KMO test to evaluate the sampling adequacy. The smallest KMO measure is 0.69 (for two items only) while the majority of items had a measure greater than 0.75. The overall KMO for the complete model is 0.78. This indicates that the proportion of the common variance is low and that data are suitable for PCA. After confirming the sample adequacy, exploratory factor analysis and parallel analysis with 1,000 repetitions was performed to detect the number of underlying factors. Figure 2 shows the scree plot and the results of the parallel analysis. The appropriate number of the factors is five as the dashed line for parallel analysis crosses the PCA line just after the fifth component. It is worth noting that by considering the Kaiser-Guttman criterion or the scree plot alone, we would reach a similar number of factors.

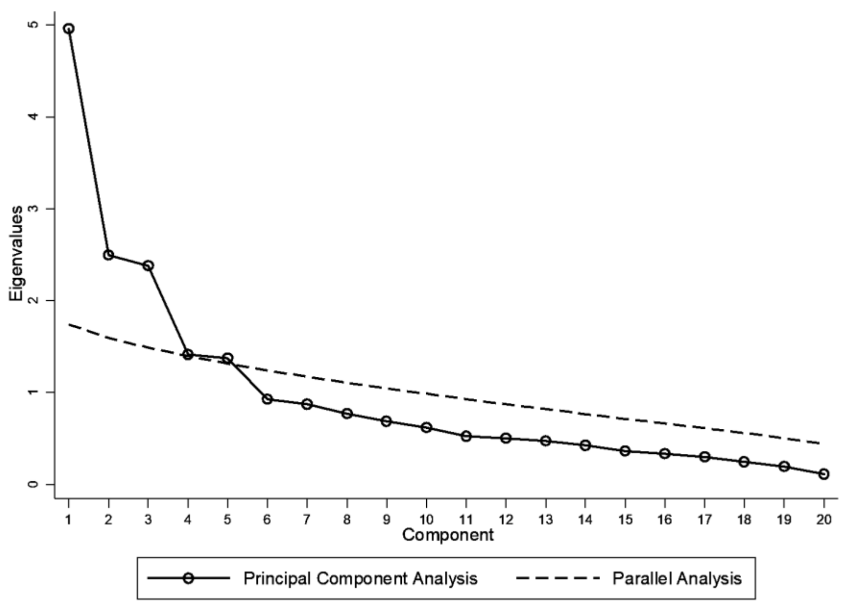

Figure 2. Scree plot of the results of parallel analysis with 1,000 repetitions

Table 1 shows the results of the exploratory factor analysis. All factor loadings are greater than the 0.4 threshold and they all load on a single factor (no cross loadings with values greater than 0.3). The Cronbach’s alpha values confirm the internal consistency reliability of the measures.

Construct	***Measure***	***Factor Loading***	***Cronbach’s Alpha***
	Total new product development costs as a percentage of sales	0.59	0.76

Innovation performance	Employee performance on health and safety, quality of life, motivation and satisfaction, knowledge and skills	0.77	
	Project planning accuracy (e.g. percentage of projects over-running planned project lead time, time-to-market or budget)	0.78	
	Development of environmental-friendly products	0.81	
Exploitation	Strengthen and upgrade current knowledge and skills for familiar production processes and technologies	0.77	0.83
	Invest in incrementally improved equipment, tools and techniques to improve the performance of our production processes	0.85	
	Acquire state-of-the-art knowledge, skills, equipment, tools and techniques	0.78	
	Acquire new managerial and organizational skills that are important for production	0.72	
Exploration	Use clear project targets, project phase standards and project management regulations for our product development activities	0.55	0.73
	Support and encourage creativity, inventiveness and participation in product innovation and improvement	0.85	
	Invite and use feedback and ideas from external partners (customers, suppliers, research institutes) to improve product development practices and performance	0.80	
	Adapt to changes in the competitive environment by innovating products	0.66	
Investments in SMT	Computer-Aided Process Planning (CAPP)	0.74	0.74
	Automatic identification / Bar code systems / RFId / Industrial IoT	0.68	
	"Smart" ICT applications supporting collaboration, connectivity, data processing, information mining, modeling, simulation	0.64	
	Manufacturing Resource Planning (MRP) and/or Enterprise Resource Planning (ERP)	0.61	
	Advanced manufacturing technologies, additive manufacturing, 3D printing, high precision technologies (micro/nano-processing)	0.59	
Business performance	Average performance, in terms of net profit, relative to the main competitor over the past three years	0.94	0.92
	Average performance, in terms of return on profit growth, relative to the main competitor over the past three years	0.92	
	Average performance, in terms of return on sales, relative to the main competitor over the past three years	0.87	

Table 1. Results of exploratory factor analysis

5.2 Confirmatory factor analysis

We considered five nested models with various number of factors. In particular, we considered (a) a single factor model that incorporates all the five constructs; (b) a two-factor model combining business performance and innovation performance (factor 1), exploration, exploitation and Smart Manufacturing Technologies (factor 2); (c) a three-factor model combining business performance and innovation performance (factor 1), exploration and exploitation (factor 2) and Smart Manufacturing Technologies (factor 3); (d) a four-factor model that combines innovation performance and business performance and finally (e) a model that consider each construct as a separate factor. The fit indexes of the models are presented in Table 2 and confirm that the 5 factors model is the only one with a good fit (for all the indexes). Thus, it is the best approach as the measurement part of our model. The factor loadings of all items were significant at $p < 0.01$.

Model	*CFI*	*TLI*	*RAMSEA*	*SRMR*	χ^2	*df*	*Difference*
1 factor	0.393	0.322	0.162	0.182	792.053	170	
2 factors	0.673	0.632	0.119	0.128	504.301	169	287.752*
3 factors	0.727	0.690	0.109	0.124	446.392	167	57.909*
4 factors	0.838	0.813	0.085	0.108	329.708	164	116.684*
5 factors	0.971	0.965	0.037	0.063	189.927	160	139.781*

Note: CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; RMSEA = Root Mean Square Error of Approximation; SRMR= Standardized
*Root Mean Squared Residual; Difference = difference in chi-square between the consecutive models; * = Significant at p < 0.01*

Table 2. Results of the confirmatory factor analysis

Table 3 shows the composite reliability of the constructs as well as the correlations among them. To further test the discriminant validity of the measures, we followed the approach of Fornell and Larcker (1981). We checked that the average variance extracted of each latent construct is larger than the squared correlation of the same latent construct with any other construct. Results confirm that each variable has more common variance with its own items than with any other four latent constructs included in the model.

Variables	*Composite reliability*	*Business Performance*	*Innovation Performance*	*Exploration*	*Exploitation*	*Investments in SMT*
Business Performance	0.81	1				
Innovation Performance	0.77	0.28*	1			
Exploration	0.76	0.03	0.38*	1		
Exploitation	0.83	0.30*	0.22*	0.27*	1	
Investments in SMT	0.74	0.29*	0.18*	0.28*	0.59*	1

** = Significant at p < 0.05*

Table 3. Composite reliability and correlations among variables

Before calculating the ambidexterity measure, according to Eq. 1, we standardized both exploration and exploitation latent variables. This reduces the correlation between the ambidexterity measures and the exploration and exploitation latent variables hence mitigates the potential for multicollinearity between the variables. This approach is also used by Cao et al. (2009) for the combined dimension of the ambidexterity. The correlation coefficients between the Ambidexterity measure of Eq. 1 and exploration and exploitation variables are 0.46 and 0.45 respectively. The correlation coefficients are below 0.5 and far smaller than 0.65 threshold, which indicates potential for multicollinearity (Tabachnick, Ullman, and Fidell 2001).

5.3 Path analysis

Figure 3 depicts the structural model of the relationship between the various constructs. The hypothesized model showed good fit to the data ($\chi^2(430) = 1{,}560.635$, CFI = 0.90, SRMR = 0.086 and RMSEA = 0.048).

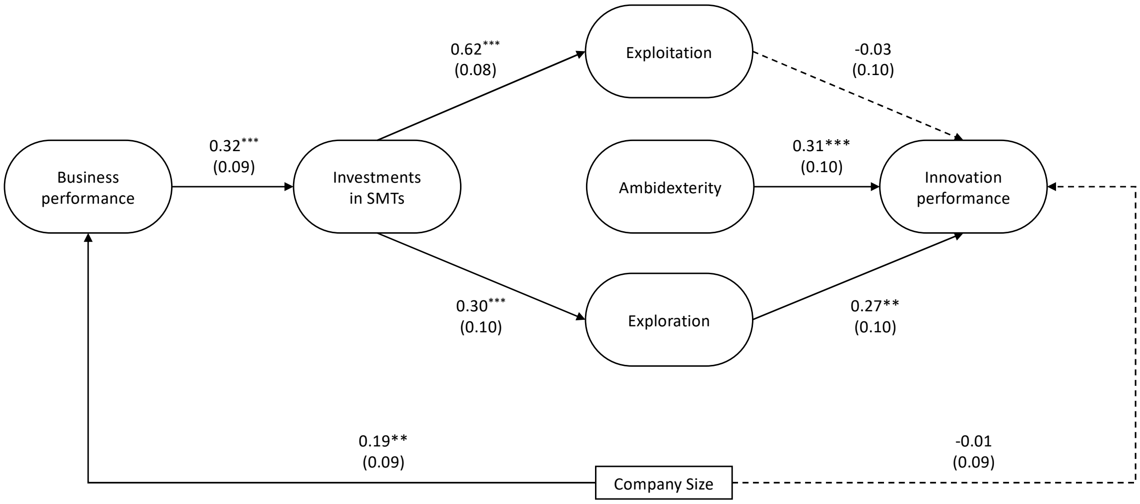

Figure 3. SEM results of the hypothesized model

Notes: Standardized coefficients are reported, with standard errors in the parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. *We have omitted the control variables associated to industries and regions in order to not complicate the figure*

Results indicate that business performance is positively related to smart manufacturing technologies ($\beta = 0.32$, $p < 0.01$). We find that smart manufacturing technologies significantly and positively affect both exploitation ($\beta = 0.62$, $p < 0.01$) and exploration ($\beta = 30$, $p < 0.01$). The model indicates that exploration is positively related to innovation performance ($\beta = 0.27$, $p < 0.05$) but that the effect of exploitation on innovation performance is insignificant ($\beta = -0.03$). This is exactly in line with the findings of Cao et al. (2009). The effect of ambidexterity on innovation performance is also positive and significant ($\beta = 0.31$, $p < 0.01$). It is worth noting that the coefficient of ambidexterity is greater than the coefficient of exploration construct ($\beta = 0.31$ for ambidexterity vs $\beta = 0.27$ for exploration). These coefficients are standardized and thus comparable. So, when it comes to increasing innovation performance, improving the ambidexterity would be more effective than increasing the exploration alone.

As for the control variables, the company size has a significant effect on the business performance ($\beta = 0.19$, $p < 0.05$), but an insignificant one on innovation performance ($\beta = -0.01$). The coefficients of the dummy variable of South America on innovation performance is significant and negative ($\beta = -0.37$, $p < 0.01$), indicating that in our sample companies in this region performed worse than the companies in Asia (the reference category). Similarly, the coefficient of South America on business performance is negative and significant ($\beta = -0.16$, $p < 0.1$). There are no significant differences in innovation performance across industries. In terms of business performance, the coefficient corresponding to industry 5 (Electrical components) is negative and significant ($\beta = -0.29$, $p < 0.05$) when compared to industry 1 (food products manufacturing, the reference category).

6. DISCUSSION

By analyzing the numerical results above, several insights to the extant theory on ambidexterity and Industry 4.0 are obtained.

Focusing on the theoretical perspective, four main contribution can be highlighted. First of all, the outcomes of the statistical analyses highlight how Industry 4.0 positively affects the capability of simultaneously pursuing exploitation and exploration strategies within different departments, thus fostering structural ambidexterity in the intra-organizational level. Secondly, the research demonstrates that structural separation positively influences innovation performance. As a third evidence, the impacts of achieving good business performances over the ability of an enterprise to invest in innovation and thus obtaining brilliant innovation performance is demonstrated. Lastly, an innovative way to operationalize ambidexterity in SEM path analysis is proposed; the method proposed could go beyond the dual theory of balance and combined dimensions, which led several authors to calculate ambidexterity as the multiplication or the absolute difference between the two strategies. The new formula proposed into this paper, on the other hand, turned out to be a reliable solution to prevent the dangerous issue of multicollinearity and to simultaneously consider the combined and balance dimensions' perspectives.

Deeply connected with the scientific implications, the performed study can provide useful managerial suggestions and thus support the decision-makers of enterprises. The first and more important implication is concerning SMTs as enabler for ambidexterity. SMTs can have an impact on both short term (business performance) and long term (innovation performances). Their evaluation should be addressed with suitable KPIs and considering a wider range of strategic considerations, and not just focusing on efficiency gains, cost savings and short-term payback. As a second practical implication, the conducted study shifts the focus on the structural conception of ambidexterity. Managers should consider the organizational separation as a practicable and reliable solution to make the company ambidextrous. In practical terms, this suggestion is in line with the model proposed by Tumino et al. (2017), according to which data coming from digital assets in factories or from the connected products on field can be engaged in operational efficiency projects (exploit) but also in new product or new services design project (explore), and these two strategies should have specialized management, targets and KPIs.

This study also emphasises the relevance of business performance on the chances of successful ambidexterity projects. Thus, managers of well-performing enterprises – from a monetary point of view – should invest the financial assets to keep up with the technological changes which are taking place globally.

Finally, some interesting evidence for managers is also stemming from the analysis of the control variables. The SEM path analysis illustrates how the context (geographical area, country) in which organizations are operating in has an influence in the possibility of achieving brilliant innovation performance. Eventually, as discussed in Section 4, the statistical analyses reveal a null impact of the company size: this means that SMTs are ambidexterity enablers both in small and large businesses (and this is a strong message from a managerial viewpoint, as small businesses are usually deemed to be less capable to handle and to leverage on complex technological investment).

7. CONCLUSIONS

Several interesting conclusions are stemming from the statistical analysis. The adoption of SMT positively affects the capability of simultaneously pursuing exploitation and exploration strategies within different departments, thus fostering structural ambidexterity. Moreover, results shed light on the ambiguous relationship between structural ambidexterity and innovation performances: our analysis clarifies that, by pursuing structural ambidexterity, i.e. by combining exploitation within the operations function and exploration within the innovation function, companies can increase their innovation performance, thus filling another literature gap. Then, the impacts of achieving good business performances over the ability of an enterprise to invest in innovation and thus obtaining brilliant innovation performance is demonstrated.

Our results shed a novel light on the current debate over industry 4.0 transition, with implications also for practitioners and manufacturing companies, as payback for expensive investments in SMT should be searched not only in improved short-term business performances, but also in better long-term innovation performances.

There are some limitations that should be considered when interpreting the results of this research. The sample included incomplete responses – i.e. missing values – which have been removed and this reduced the sample available to test the hypotheses. The questionnaire used to test our assumptions was referred to a given timeframe – i.e. the last three years performance of the firm - while it would have been better to measure firms' innovation performance after a longer time interval with respect to business performance.

We envision several avenues for further investigations. Similar research can be conducted on a larger sample of countries to have a more comprehensive perspective on performance differences. Moreover, it would be interesting to assess the impact of each single SMT over structural ambidexterity and thus innovation performance. For instance, the effects of adopting additive manufacturing could be compared with the ones stemming from the implementation of cloud manufacturing; by comparing the results, it would be possible to understand which SMT is the most suitable to foster the simultaneous implementation of exploitation and exploration within the firm.

REFERENCES

Adler, Paul S, Mary Benner, David James Brunner, John Paul MacDuffie, Emi Osono, Bradley R Staats, Hirotaka Takeuchi, Michael Tushman, and Sidney G Winter. 2009. Perspectives on the Productivity Dilemma. J. of Operations Management 27 (2): 99–113.

Akman, Gülşen, and Cengiz Yilmaz. 2008. Innovative Capability, Innovation Strategy and Market Orientation: An Empirical Analysis in Turkish Software Industry. International J. of Innovation Management 12 (01): 69–111.

Ali, A B M Shawkat, and Salahuddin Azad. 2013. Demand Forecasting in Smart Grid. In Smart Grids, 135–50. Springer.

Anderson, James C, and David W Gerbing. 1988. Structural Equation Modeling in Practice: A Review and Recommended Two-Step Approach. Psychological Bulletin 103 (3): 411.

Andriopoulos, Constantine, and Marianne W Lewis. 2009. Exploitation-Exploration Tensions and Organizational Ambidexterity: Managing Paradoxes of Innovation. Organization Science 20 (4): 696–717.

Armstrong, J Scott, and Terry S Overton. 1977. Estimating Nonresponse Bias in Mail Surveys. J. of Marketing Research 14 (3): 396–402.

Atuahene-Gima, Kwaku. 2005. Resolving the Capability–Rigidity Paradox in New Product Innovation. J. of Marketing 69 (4): 61–83.

Atuahene-Gima, Kwaku, and Janet Y Murray. 2007. Exploratory and Exploitative Learning in New Product Development: A Social Capital Perspective on New Technology Ventures in China. J. of International Marketing 15 (2): 1–29.
Benner, Mary J, and Michael Tushman. 2002. Process Management and Technological Innovation: A Longitudinal Study of the Photography and Paint Industries. Administrative Science Quarterly 47 (4): 676–707.
Bentler, Peter M. 1990. Comparative Fit Indexes in Structural Models. Psychological Bulletin 107 (2): 238.
Bodwell, Wendy, and Thomas J Chermack. 2010. Organizational Ambidexterity: Integrating Deliberate and Emergent Strategy with Scenario Planning. Technological Forecasting and Social Change 77 (2): 193–202.
Bottani, Eleonora. 2010. Profile and Enablers of Agile Companies: An Empirical Investigation. International J. of Production Economics 125 (2): 251–61.
Bressanelli, Gianmarco, Federico Adrodegari, Marco Perona, and Nicola Saccani. 2018. Exploring How Usage-Focused Business Models Enable Circular Economy through Digital Technologies. Sustainability (Switzerland) 10 (3).
Brousell, D. R., J. R. Moad, and P. Tate. 2014. The Next Industrial Revolution: How the Internet of Things and Embedded, Connected, Intelligent Devices Will Transform Manufacturing. https://www.allegient.com/wp-content/uploads/FS_ Industrial_revolution.pdf.
Browne, Michael W, and Robert Cudeck. 1989. Single Sample Cross-Validation Indices for Covariance Structures. Multivariate Behavioral Research 24 (4): 445–55.
Cao, Qing, Eric Gedajlovic, and Hongping Zhang. 2009. Unpacking Organizational Ambidexterity: Dimensions, Contingencies, and Synergistic Effects. Organization Science 20 (4): 781–96.
Cerny, Barbara A, and Henry F Kaiser. 1977. A Study of a Measure of Sampling Adequacy for Factor-Analytic Correlation Matrices. Multivariate Behavioral Research 12 (1): 43–47.
Chaudhuri, Surajit, Umeshwar Dayal, and Vivek Narasayya. 2011. An Overview of Business Intelligence Technology. Communications of the ACM 54 (8): 88–98.
Culot, Giovanna, Guido Nassimbeni, Guido Orzes, and Marco Sartor. 2020. Behind the Definition of Industry 4.0: Analysis and Open Questions. International J. of Production Economics 226 (August 2018): 107617.
Dalenogare, Lucas Santos, Guilherme Brittes Benitez, Néstor Fabián Ayala, and Alejandro Germán Frank. 2018. The Expected Contribution of Industry 4.0 Technologies for Industrial Performance. International J. of Production Economics 204 (1): 383–94.
Duncan, R. B. 1976. The Ambidextrous Organization: Designing Dual Structures for Innovation. The Management of Organization 1: 167–88.
Eisenhardt, Kathleen M, Nathan R Furr, and Christopher B Bingham. 2010. CROSSROADS—Microfoundations of Performance: Balancing Efficiency and Flexibility in Dynamic Environments. Organization Science 21 (6): 1263–73.
Fornell, Claes, and David F Larcker. 1981. Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. J. of Marketing Research 18 (1): 39–50.
Frank, Alejandro Germán, Lucas Santos Dalenogare, and Néstor Fabián Ayala. 2019. Industry 4.0 Technologies: Implementation Patterns in Manufacturing Companies. International J. of Production Economics 210 (January): 15–26.
Frank, Alejandro Germán, Glauco H S Mendes, Néstor F Ayala, and Antonio Ghezzi. 2019.

Servitization and Industry 4.0 Convergence in the Digital Transformation of Product Firms: A Business Model Innovation Perspective. Technological Forecasting and Social Change 141: 341–51.
Gastaldi, Luca, Francesco Paolo Appio, Mariano Corso, and Andrea Pistorio. 2018. Managing the Exploration-Exploitation Paradox in Healthcare. Business Process Management J. 24 (5): 1200–1234.
Gastaldi, Luca, Riccardo Mangiaracina, Giovanni Miragliotta, Alessandro Perego, and Angela Tumino. 2015. Measuring the Benefits of Tracking Medical Treatment through RFId. International J. of Productivity and Performance Management 64 (2): 175–93.
Gibson, Cristina B, and Julian Birkinshaw. 2004. The Antecedents, Consequences, and Mediating Role of Organizational Ambidexterity. Academy of Management J. 47 (2): 209–26.
Griffin, Abbie, and Albert L Page. 1993. An Interim Report on Measuring Product Development Success and Failure. J. of Product Innovation Management 10 (4): 291–308.
Hair, Joseph F, William C Black, Barry J Babin, Rolph E Anderson, and Ronald L Tatham. 2006. Multivariate Data Analysis. Vol. 5. Prentice hall Upper Saddle River, NJ.
Halse, Lise Lillebrygfjeld, and Eli Fyhn Ullern. 2017. Getting Ready for the Fourth Industrial Revolution: Innovation in Small and Medium Sized Companies. In Advances in Production Management Systems.: The Path to Intelligent, Collaborative and Sustainable Manufacturing. APMS 2017. IFIP Advances in Information and Communication,Vol 513 Technology, edited by Kiritsis D. Lödding H., Riedel R., Thoben KD., von Cieminski G., 247–54. Springer.
Hayton, James C, David G Allen, and Vida Scarpello. 2004. Factor Retention Decisions in Exploratory Factor Analysis: A Tutorial on Parallel Analysis. Organizational Research Methods 7 (2): 191–205.
He, Zi-Lin, and Poh-Kam Wong. 2004. Exploration vs. Exploitation: An Empirical Test of the Ambidexterity Hypothesis. Organization Science 15 (4): 481–94.
Jeschke, Sabina, Christian Brecher, Tobias Meisen, Denis Özdemir, and Tim Eschert. 2017. Industrial Internet of Things and Cyber Manufacturing Systems. In Industrial Internet of Things, 3–19. Springer.
Katila, Riitta, and Gautam Ahuja. 2002. Something Old, Something New: A Longitudinal Study of Search Behavior and New Product Introduction. Academy of Management J. 45 (6): 1183–94.
Kim, Hyunho, Boncho Ku, Jong Yeol Kim, Young-Jae Park, and Young-Bae Park. 2016. Confirmatory and Exploratory Factor Analysis for Validating the Phlegm Pattern Questionnaire for Healthy Subjects. Evidence-Based Complementary and Alternative Medicine 2016: 1–8.
Kline, Rex B. 1998. Software Review: Software Programs for Structural Equation Modeling: Amos, EQS, and LISREL. J. of Psychoeducational Assessment 16 (4): 343–64.
Lavie, Dovev, Uriel Stettner, and Michael L Tushman. 2010. Exploration and Exploitation within and across Organizations. Academy of Management Annals 4 (1): 109–55.
Lee, Ryeowon, Jong-Ho Lee, and Tony C Garrett. 2019. Synergy Effects of Innovation on Firm Performance. J. of Business Research 99 (1): 507–15.
Levinthal, Daniel A., and James G. March. 1993. The Myopia of Learning. Strategic Management J. 14 (2 S): 95–112.
Li, Ci-Rong, Chih-Peng Chu, and Chen-Ju Lin. 2010. The Contingent Value of Exploratory

and Exploitative Learning for New Product Development Performance. Industrial Marketing Management 39 (7): 1186–97.
Lin, Angela, and Nan-Chou Chen. 2012. Cloud Computing as an Innovation: Percepetion, Attitude, and Adoption. International J. of Information Management 32 (6): 533–40.
Lu, Yang. 2017. Industry 4.0: A Survey on Technologies, Applications and Open Research Issues. J. of Industrial Information Integration 6 (1): 1–10.
Lubatkin, Michael H, Zeki Simsek, Yan Ling, and John F Veiga. 2006. Ambidexterity and Performance in Small-to Medium-Sized Firms: The Pivotal Role of Top Management Team Behavioral Integration. J. of Management 32 (5): 646–72.
Malhotra, Yogesh. 2001. Organizational Controls as Enablers and Constraints in Successful Knowledge Management Systems Implementation. In Knowledge Management and Business Model Innovation, 326–36. IGI Global.
March, J.G. 1991. Exploration and Exploitation in Organizational Learning. Organization Science 2 (1): 71–87.
McDougall, Robert, and Rod Tyers. 1994. Asian Expansion and Labor-Saving Technical Change: Factor Market Effects and Policy Reactions. American J. of Agricultural Economics 76 (5): 1111–18.
Medsker, Gina J, Larry J Williams, and Patricia J Holahan. 1994. A Review of Current Practices for Evaluating Causal Models in Organizational Behavior and Human Resources Management Research. J. of Management 20 (2): 439–64.
Miragliotta, Giovanni, and Fadi Shrouf. 2013. Using Internet of Things to Improve Eco-Efficiency in Manufacturing: A Review on Available Knowledge and a Framework for IoT Adoption. In Advances in Production Management Systems. Competitive Manufacturing for Innovative Products and Services. IFIP Advances in Information and Communication Technology, edited by C Emmanouilidis, M Taisch, and D Kiritsis, 397:96–102. Berlin, Heidelberg: Springer.
Miragliotta, Giovanni, Andrea Sianesi, Elisa Convertini, and Rossella Distante. 2018. Data Driven Management in Industry 4.0: A Method to Measure Data Productivity. IFAC-PapersOnLine 51 (11): 19–24.
Müller, Julian Marius, Daniel Kiel, and Kai-Ingo Voigt. 2018. What Drives the Implementation of Industry 4.0? The Role of Opportunities and Challenges in the Context of Sustainability. Sustainability 10 (1): 247.
Nerkar, Atul. 2003. Old Is Gold? The Value of Temporal Exploration in the Creation of New Knowledge. Management Science 49 (2): 211–29.
Ossenbrink, Jan, Joern Hoppmann, and Volker H Hoffmann. 2019. Hybrid Ambidexterity: How the Environment Shapes Incumbents' Use of Structural and Contextual Approaches. Organization Science 30 (6): 1319–48.
Piening, Erk P, and Torsten Oliver Salge. 2015. Understanding the Antecedents, Contingencies, and Performance Implications of Process Innovation: A Dynamic Capabilities Perspective. J. of Product Innovation Management 32 (1): 80–97.
Prajogo, Daniel I, and Pervaiz K Ahmed. 2006. Relationships between Innovation Stimulus, Innovation Capacity, and Innovation Performance. R&D Management 36 (5): 499–515.
Pullman, Madeleine E, Michael J Maloni, and Craig R Carter. 2009. Food for Thought: Social versus Environmental Sustainability Practices and Performance Outcomes. J. of Supply Chain Management 45 (4): 38–54.

Raisch, Sebastian, and Julian Birkinshaw. 2008. Organizational Ambidexterity: Antecedents, Outcomes, and Moderators. J. of Management 34 (3): 375–409.
Schreyögg, Georg, and Jörg Sydow. 2010. Crossroads—Organizing for Fluidity? Dilemmas of New Organizational Forms. Organization Science 21 (6): 1251–62.
Sharfman, Mark P, Gerrit Wolf, Richard B Chase, and David A Tansik. 1988. Antecedents of Organizational Slack. Academy of Management Review 13 (4): 601–14.
Simsek, Zeki. 2009. Organizational Ambidexterity: Towards a Multilevel Understanding. J. of Management Studies 46 (4): 597–624.
Sousa Jabbour, Ana Beatriz Lopes de, Charbel Jose Chiappetta Jabbour, Cyril Foropon, and Moacir Godinho Filho. 2018. When Titans Meet–Can Industry 4.0 Revolutionise the Environmentally-Sustainable Manufacturing Wave? The Role of Critical Success Factors. Technological Forecasting and Social Change 132: 18–25.
Steiger, James H. 1990. Structural Model Evaluation and Modification: An Interval Estimation Approach. Multivariate Behavioral Research 25 (2): 173–80.
Stein, Eric W, and Vladimir Zwass. 1995. Actualizing Organizational Memory with Information Systems. Information Systems Research 6 (2): 85–117.
Szalavetz, Andrea. 2019. Industry 4.0 and Capability Development in Manufacturing Subsidiaries. Technological Forecasting and Social Change 145 (July 2017): 384–95.
Tabachnick, B G, J B Ullman, and L S Fidell. 2001. Using Multivariate Statistics (4th Ed). Boston, MA: Pearson. Allyn and Bacon Needham Heights, MA.
Tedaldi, Gianluca, and Giovanni Miragliotta. 2020. The Role of Engineering-to-Order Machinery Manufacturers in Future Cloud Manufacturing Supply Chains: A Business Case and a Strategic Perspective. Production Planning and Control 1 (1): 1. https://doi.org/10.1080/09537287.2020.1837942.
Tumino, Angela, Giovanni Miragliotta, and Giulio Salvadori. 2017. Internet of Things: Beyond Objects, toward Services.
Vázquez-Bustelo, Daniel, Lucía Avella, and Esteban Fernández. 2007. Agility Drivers, Enablers and Outcomes. International J. of Operations & Production Management 27 (12): 1303–1332.
Wong, Veronica, William Turner, and Paul Stoneman. 1996. Marketing Strategies and Market Prospects for Environmentally-friendly Consumer Products 1. British J. of Management 7 (3): 263–81.
Xu, Li Da, and Lian Duan. 2019. Big Data for Cyber Physical Systems in Industry 4.0: A Survey. Enterprise Information Systems 13 (2): 148–69.
Xue, Ling, Gautam Ray, and Vallabh Sambamurthy. 2012. Efficiency or Innovation: How Do Industry Environments Moderate the Effects of Firms’ IT Asset Portfolios? MIS Quarterly 36 (2): 509–28.