Companies' adoption of Smart Technologies to achieve structural ambidexterity: an analysis with SEM

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Abstract

The transition to "Industry 4.0" and the adoption of Smart Technologies (STs) are generally driven by expectations of gains in productivity, better control over operations and supply chain processes and, therefore, improved competitiveness. These factors are important 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. The ambidextrous balancing of these two areas requires concerted effort and the capacity to balance paradoxical tensions. Literature has thoroughly covered the aspect of how to overcome the trade-off between exploitation and exploration. However, research has only recently started focusing on the pivotal role that digital technologies may play in this process. Our paper contributes to this nascent literature stream by investigating how STs can operate as antecedents of structural ambidexterity. This study relies on the 3rd CINet Survey (2016-2017) involving over 370 companies worldwide. Leveraging on STs and structural ambidexterity as mediators, we used Structural Equation Modelling to show that manufacturing firms with good business performance are in a favorable position to achieve better innovation performances. Our results shed new light on the current debate around the Industry 4.0 transition, with implications for both academics and practitioners.

1. Introduction

Manufacturing firms have evolved incredibly over the past century. Their key mission shifted from enlarging their production scale, in the 1960s, to reducing production costs and promoting product quality, in the 1970-80s (Zhang et al., 2014). All their effort went in the direction of exploiting their manufacturing assets as fully as possible, while all the time improving the firm's productivity and efficiency. In the 1990s, with the increasing level of competition, it became clear that productivity and efficiency were no longer enough to sustain competitive advantage; the need to be extremely flexible and responsive intensified and, as highlighted by Gunasekaran (1999), agility, a firm's capacity to redirect its strategic focus, reacting quickly and effectively to ever-changing turbulent markets, became a fundamental axiom. The capability of exploring new and innovative ways of creating value became pivotal even in manufacturing firms (Gunday et al., 2011).

Nowadays, manufacturing companies are facing the Fourth Industrial Revolution, which can be summarized as the convolution of physical and digital realities into a single, complex competitive playground characterized by continuous technological innovation (Culot et al., 2020). In this scenario, firms are increasingly pushed to be efficient and competitive in the short term, as well as flexible and innovative in the long term; in other words, they need to be ambidextrous (Bodwell and Chermack, 2010; Derbyshire, 2014). Ambidexterity is ''the ability of an organization to both explore and exploit: to compete in mature technologies and markets where efficiency, control, and incremental improvement are prized, and also to compete in new technologies and markets where flexibility, autonomy and experimentation are needed'' (O'Reilly and Tushman, 2013).

Companies in every sector are asked to develop ambidexterity to cope with today's business challenges (Martini et al., 2013), and this is particularly true for manufacturing firms, which must excel in quite traditional operational performance areas (cost efficiency, punctuality and quality, to name a few) and, at the same time, pursue product and process innovation as never before (Herzallah et al., 2017).

The literature has thoroughly investigated how to overcome the trade-off between exploitation and exploration, distinguishing reconciling actions at both intra- and inter-organizational levels (Petruzzelli, 2019). Our study focuses on the intra-organizational level, where research has started to focus on the crucial role that digital technologies may have in this process (Gastaldi et al., 2018; Park et al., 2020). In this regard, manufacturing once again stands out as a very interesting context, because of the expected role of digital technologies in driving efficiency and innovation, as suggested by the Industry 4.0 paradigm (Dalenogare et al., 2018).

This expectation was checked through a literature review that investigated both ambidexterity and Industry 4.0. Its twofold purpose was, on the one hand, to identify all possible ambidexterity configurations, their antecedents, their effects and how they can be operationalized, and, on the other, to understand the impact of Industry 4.0 on companies that are adopting this new business model.

A main research gap arose from the literature review, that of understanding whether investment in Industry 4.0 enables companies to be ambidextrous, and thus to pursue exploitation and exploration at the same time. The importance of decision-makers has already been demonstrated and remains fundamental, being what really drives ambidexterity in practice (Tushman et al., 2011; Mazzelli et al., 2020). However, we question whether digital technologies could enable and leverage on ambidexterity. Providing evidence of this relationship could be a significant contribution, and help manufacturing firms to find better balance when justifying the investment needed for their digitization programs. If ambidexterity were proven, it would mean that investment payback should be pursued not only by improving short-term business performance but also through better long-term innovation performance. To achieve our purpose, we leveraged on data collected in the 3rd CINet Survey, administered from November 2016 to June 2017 and involving over 370 companies worldwide. Leveraging on innovative technologies and structural ambidexterity as mediators, we used Structural Equation Modelling to find evidence that manufacturing firms with good business performance are in a favorable position to achieve better innovation performance. Our results shed new light on the current debate over Industry 4.0 transition, with implications for both academics and practitioners.

2. Theoretical background

2.1. Ambidexterity

In organizational studies, the term “ambidexterity” was first introduced by Duncan (1976), but scientific debate around the concept started in 1991, when March proposed the constructs “exploitation” and “exploration” to identify the two divergent strategies that constitute ambidexterity. Exploitation means leveraging on existing resources and is about consolidating, refining and becoming more efficient in the utilization of existing resources (e.g. equipment, knowledge), while exploration represents the way companies search for new opportunities and get out of their “comfort zone” by pursuing variation, taking risks and experimenting (March, 1991). The importance of being ambidextrous comes from the fact that firms cannot just engage in exploiting their current assets, because sustained competitive advantage cannot rely on static competencies alone, as these tend to become obsolete. At the same time, companies that focus only on exploration would never gain any return on their current assets. The right balance between exploration and exploitation is difficult to achieve and to be maintained (Levinthal and March, 1993).

Despite having originated within organizational studies, the constructs of exploration, exploitation and ambidexterity are overspilling into manufacturing literature, and currently there is a moderate consensus about the merits of this balancing process (Lavie et al., 2010). There is, however, little agreement on the means whereby organizations pursue this balance, including outside the manufacturing domain (Adler et al., 2009). Ambidexterity could be achieved, within a single firm, by using internal resources or leveraging on external actors (i.e. suppliers, customers, competitors) as described by Ardito et al. (2020). Only when the focus is on intra-firm balancing processes does the literature divide into two approaches (Eisenhardt et al., 2010; Schreyögg and Sydow, 2010), which differ in terms of their emphasis being on differentiation or on integration when addressing the diverging alternatives (Andriopoulos and Lewis, 2009).

On the one side, there are the structural approaches to ambidexterity, which stress the use of structure and strategy to enable differentiation among organizational units. Segregated efforts target either one or the other dichotomous activity (Andriopoulos and Lewis, 2009). As an example, in manufacturing firms it is common to find an Innovation (or R&D) department, mainly concerned with exploring new products and processes, while the objective of an Operations department is to increase efficiency in the production processes. Blindenbach-Driessen and Van Den Ende (2014) show that this structural approach increases exploration, exploitation and ambidexterity in both manufacturing and service firms.

On the other side, there are the contextual approaches to ambidexterity, which — mostly rooted in the organizational learning and innovation management literature streams — utilize behavioral, cognitive and social means to integrate diverging activities (Eisenhardt et al., 2010; Gibson and Birkinshaw, 2004). In manufacturing industries, for instance, an operations manager will apply a contextual approach when asking line managers and their teams to apply lean production practices as a strategy to explore new ways of generating value while exploiting their current assets (Secchi and Camuffo, 2019). Recently scholars have developed hybrid models, which combine aspects coming from both structural and contextual ambidexterity (Ossenbrink et al., 2019).

In the manufacturing context, a capacity for ambidexterity becomes relevant when it can affect business performance positively (Derbyshire, 2014). He and Wong (2004) have provided strong empirical evidence of the positive effect of ambidexterity on sales growth rates in manufacturing firms. Nowadays, these firms are facing an increasingly dynamic and complex environment where ambidexterity, together with absorptive capacity (Tu et al., 2006), can produce a greater competitive advantage. Patel et al. (2012) have demonstrated that firms that can absorb external knowledge and pursue ambidextrous capabilities are better positioned to leverage on manufacturing flexibility so as to achieve higher performance outcomes. Lastly, Vilkas et al. (2021) have shown that lean production can be viewed in the light of ambidexterity as it (i) actually contributes to both incremental and radical process improvement and (ii) facilitates both exploration and exploitation processes.

After having outlined the concept of ambidexterity and its manufacturing contextualization, it was important for us to give an overview on how ambidexterity is measured in the literature. Cao et al. (2009) discussed two fundamental concepts that reach beyond measurement models, "combined dimension" and "balance dimension"; nevertheless, there is no consensus about which method should be used, as ambidexterity could be measured in different ways. Given any measure of the two constructs of exploration and exploitation, any operator that could be used to obtain a score for ambidexterity shows both 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 compared to the other models (Lubatkin et al., 2006), but it neglects the perspective of the "balance dimension", as a company that scores 1 in exploitation and 6 in exploration (or vice versa) appears to be more ambidextrous than a company scoring 3 and 3, while in reality the focus should be on the combined action of the two. The multiplication operator used by several authors (e.g. Ardito et al., 2018) captures the interaction effect, but it suffers from multicollinearity (Gibson and Birkinshaw, 2004); moreover, when using multiplication, a company that scores 2 and 3 in the two strategies appears to be more ambidextrous than one scoring 2 and 2, and this is - again - partially in contrast with the idea of "balance dimension". Lastly, the "absolute value of the subtraction" operator seems to be the most accurate for balance, but, once again, a company that scores 1 in both exploration and exploitation appears to be just as ambidextrous as one scoring 5 and 5, and this is absurd. On this point, Simsek (2009) states that an organization with low levels of exploitation and exploration is balanced but not ambidextrous.

2.2. Industry 4.0 and Smart Technologies

In around 2010, academics and practitioners observed the upcoming transformation in the social and economic landscape, caused by changes to customer behavior and the maturation of new promising technologies (Brousell et al., 2014). This event has been labelled as the Fourth Industrial Revolution, and, in the manufacturing context, it has led to the term "Industry 4.0" or I4.0 (coined in Germany in 2011 and introduced publicly at the Hannover Fair to describe the German government's high-tech strategy to support German manufacturing). In our view, Industry 4.0 refers to a vision of the future in industry and manufacturing where digital and smart technologies will boost efficiency and competitiveness by interconnecting resources of every kind (data, people machinery and assets) within a factory/manufacturing organization and along the value chain (Miragliotta et al., 2018).

Today, there is moderate consensus about the Industry 4.0 concept and the Smart Technologies (STs) by which it is enabled, as highlighted by Zheng et al. (2021), Ardito et al. (2019) and Culot et al. (2020): advanced automation (e.g. collaborative robots), additive manufacturing, augmented human-machine interface technology (such as e.g.

augmented and virtual reality), simulation, cloud manufacturing (as defined by Xu, 2012, and by Tedaldi and Miragliotta, 2020), Industrial Internet of Things, big data analytics (including artificial intelligence) and cyber security.

Industry 4.0 is impacting traditional manufacturing companies in the four process areas of smart manufacturing, smart products, smart supply chain and smart working (Frank et al., 2019a; Meindl et al., 2021). Moreover, academics are studying Industry 4.0 in conjunction with other major trends, such as sustainability and servitization. De Sousa Jabbour et al. (2018) proposed a framework that takes in eleven critical factors of success which enterprises should manage when integrating Industry 4.0 and “green” (i.e. environmentally 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, in which smart technologies can open new channels for gathering data and information.

Going back to Smart Technologies (STs), a remarkable number of papers state that Industrial IoT, big data analytics and cloud are key-enablers for this manufacturing revolution (Miragliotta and Shrouf, 2013; Lasi et al., 2014). These technologies, in cooperation with existing traditional IT systems - such as Enterprise Resource Planning (ERP), computer aided process planning and product data management / product lifecycle management - and traditional automation systems belonging to the field of “Operational Technologies” (OT) - such as programmable logic controllers and supervisory control and data acquisition (SCADA) systems - are the fundamentals of today’s digital manufacturing scenario (Lu, 2017).

Today, it is universally acknowledged that STs help companies to increase efficiency within their production sites/operations (Xu and Duan, 2019), i.e. to exploit their assets better. For instance, some companies have been implementing IoT platforms to extract data in real-time from machinery and to alert operators when failure occurs, thereby avoiding worse consequences and reducing overall downtime (Sowmya et al., 2021). Other firms leverage on data produced by the machinery and develop condition-based algorithms to predict when maintenance will be needed, in order to prolong the life of machines and components and limit downtime (Shin and Jun, 2015). In parallel with this exploitation side are the many exploration activities that take place in the manufacturing domain when companies adopt STs to re-design products or processes. The introduction of any new technology, such as using additive manufacturing to accelerate new product development or produce spare parts on demand (Attaran, 2017), relates to exploration, as it requires the company to invest time, acquire new knowledge through experimentation, and take risks on the outcomes in the long-term (March, 1991). Exploration also comes into play when companies make fundamental changes to their business model enabled by STs. Bressanelli et al. (2018) explored the role of IoT and big data analytics in the introduction of new business models; they identified some functionalities linked to the circular economy paradigm - where the central aspect is the company’s capacity to innovate its products - that are enabled by these technologies.

However, companies struggle to adopt STs because of several barriers. Kamble et al. (2018) identified 12 such barriers, and arranged them according to the hierarchical relationships connecting them. Their study indicates that the most relevant barrier is the lack of a clear comprehension of the benefits (which makes investments in STs more risky), and the second most significant is the high level of investment required. Other barriers exist, both technically (e.g. lack of standards, as in Lu et al., 2020, or security issues, as in Pereira et al., 2017) and from an organizational perspective, because many processes could be changed with the introduction of STs, and operators and managers would require new skills (Pinzone et al., 2017).

2.3. Gaps and objectives of the study

The review of extant literature shows an almost complete absence of research that simultaneously considers the adoption of STs and ambidexterity in intra-organizational contexts within manufacturing firms. Halse and Ullern (2017) claim that – for a manufacturing firm – both openness to an external network of partners and organizational ambidexterity are vital for its “Industry 4.0 transformation”.

A first question then arises about the opposite relationship, i.e. the effect of STs on a firm’s ambidexterity. Szalavetz (2019) investigated the impact of advanced Industry 4.0-associated manufacturing technologies on a company’s subsidiaries, and discovered that they can contribute in two ways, in that they encourage the increase of both production capability (i.e. operating at a given level of technology with excellent operational efficiency) and R&D capabilities, but she makes no reference to the balance between the two, i.e. the ambidexterity of these subsidiaries. Mahmood and Mubarik (2020) demonstrated that intellectual capital (i.e. the knowledge, ability and strength of employees) has a profound influence over ambidexterity where Industry 4.0 and related STs are just defining the current context of transformation. Their findings show that technology absorption capability also plays a significant mediating role, but there is no reference to the actual applications of STs. While these papers evaluate the antecedents or the outcomes of ambidexterity in the Industry 4.0 era, to the best of the authors’ knowledge, no paper has investigated the effect of STs on a firm’s ambidextrous strategy. This gap is interesting to study, as today companies are adopting STs mainly to exploit their internal resources better (i.e. increase efficiency, productivity, availability of machinery etc.). Should STs prove to be the antecedents of ambidexterity, companies ought to look at them from a different perspective, considering investment in STs as an enabler for a balanced development of exploitation and exploration capabilities, thus higher competitiveness in both the short and the long term.

Gastaldi et al. (2018) and Rialti et al. (2019) share this position, but with different objectives. Gastaldi et al. (2018) analyzed how digital technologies can help hospitals to improve the exploration-exploitation dilemma over time, but their study is confined to healthcare settings, and so removed from the manufacturing context. Rialti et al. (2019) found that the capabilities developed in a company when it implements big data analytics solutions has a positive effect on its ambidexterity, but they did not address other key STs.

A second gap concerning Industry 4.0 is that many authors studying this topic focus their attention on the benefits of adopting STs, and how STs can have a positive, or potentially even negative, impact on a company’s business performance (Dalenogare et al., 2018; Gastaldi et al., 2015; Jeschke et al., 2017). Nevertheless, as suggested by Piening and Salge (2015), the opposite relationship has not been investigated, i.e. there are no studies which assess business performances as enablers for the adoption of STs and so conducive to innovation performance. This gap should be covered, since many ST applications require high investment.

A third gap is the fact that many scholars concentrate on ambidexterity, without defining how companies should behave if they are to put exploitation and exploration into practice simultaneously. He and Wong (2004) accepted that their study does not address the issue of which organizational design principles are appropriate for ambidexterity. Some scholars have argued that, if a firm aims to excel in both improving existing products and generating new ones, it should apply structural ambidexterity (Gibson and Birkinshaw, 2004; Levinthal and March, 1993; Raisch and Birkinshaw, 2008); nevertheless, no one has clearly demonstrated that structural ambidexterity can have a positive influence on innovation performance. This is relevant, as most manufacturing firms are organized with a structural subdivision, with departments dedicated mainly to exploitation (e.g. the production unit) or mainly to exploration (e.g. the R&D unit).

In brief, our study addresses a core research problem, which is the relationship between Industry 4.0, in particular the adoption of STs in manufacturing contexts, and ambidexterity; this research problem will therefore be framed across three research questions (RQs), as follows:

- RQ1: Do STs enable manufacturing firms to be ambidextrous and thus pursue strategies of exploration and exploitation simultaneously?
- RQ2: Is investing in STs an investment priority of well-performing manufacturing companies?
- RQ3: Do exploitation, exploration and structural ambidexterity have a positive impact on innovation performance in manufacturing firms?

In order to answer the outlined RQs properly, our work was conducted on the basis of a model which incorporates six hypotheses, as shown in Figure 1.

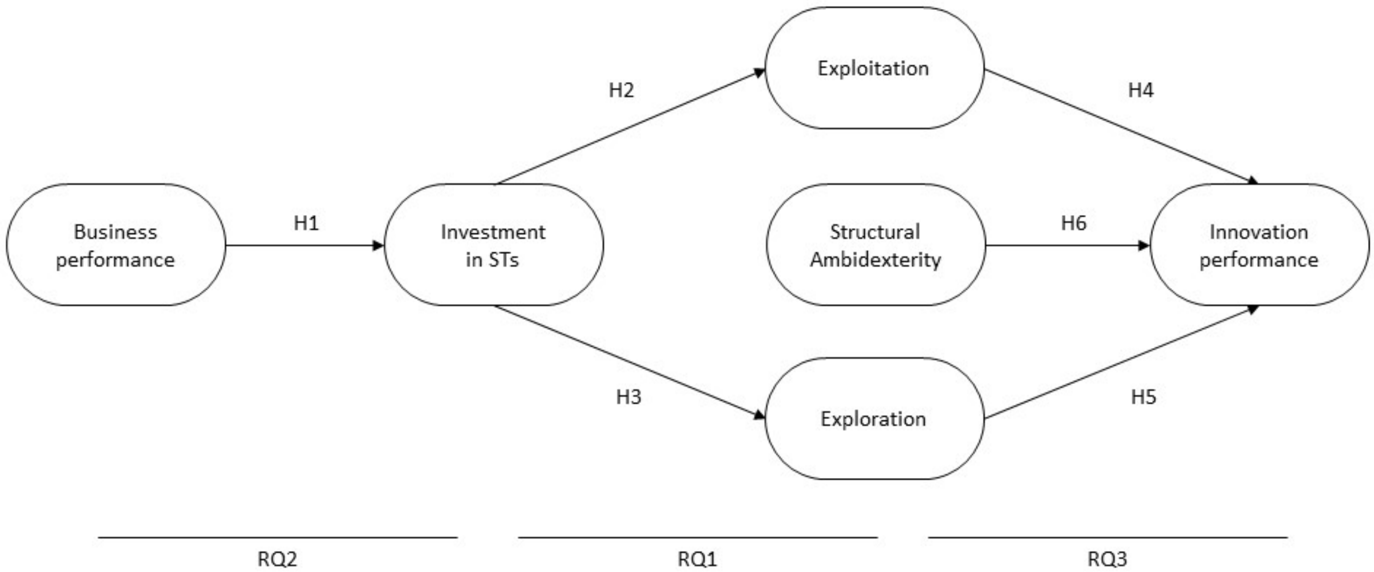

Figure 1. Research questions and hypotheses

The first hypothesis is to understand whether good business performance promotes the adoption of STs. Although it is clear that companies able to achieve good business performance are well positioned to invest (Sharfman et al., 1988), we question whether they are actually currently investing in STs, rather than continuing along more traditional courses of investment, such as conventional product development, improving/extending their distribution channels, etc. This hypothesis is rooted in the fact that ST adoption can be very costly (Lin and Chen, 2012), as it usually requires ad-hoc solutions designed for a specific company (Müller et al., 2018). The implications of this position are significant, as it could induce us to say that (financially) high performing companies could be at an advantage in this Industry 4.0 transformation. On the basis of these arguments, we defined the first hypothesis as H1:

H1. Good business performance of a manufacturing firm positively influences the implementation of STs.

The second hypothesis assumes that there is a positive relationship between STs and exploitation, which is strongly supported by the literature. Over the past decades, several authors have studied digital technologies as one of the antecedents of exploitation (Malhotra, 2001; Stein and Zwass, 1995; Xue et al., 2012). In addition, a point worth keeping in mind is that, when companies embark on digital transformation, their initial objective is generally to exploit their resources more effectively and become more efficient in terms of time savings, cost reductions and simplified management (Gastaldi et al., 2018). With respect to STs, Ali and Azad (2013) considered their benefits from an operational perspective, highlighting the optimization of time-cost trade-offs and increased energy savings, while Kang et al. (2016) generally talked about increased efficiency. Thus, H2 is:

H2. The adoption of STs has a positive influence on exploitation within a manufacturing firm.

The third hypothesis comes from evidence that, once companies can achieve the main benefits of their initial digitization investment, the digitization system introduced enables them to explore new and radical ways of providing products or services. Gastaldi et al. (2018) addressed this argument, but their work was far removed from the manufacturing context. Digital technologies are expected to improve the data collection and processing side, so organizations can respond to market changes in a timely manner and identify new business opportunities (Chaudhuri et al., 2011). On the basis of these arguments, the next hypothesis is as follows:

H3. The adoption of STs has a positive influence on exploration within a manufacturing firm.

Concerning the fourth hypothesis, it is acknowledged that exploitation enhances short-term performance (Atuahene-Gima, 2005) but, at the same time, some authors have found that exploitation can also have a 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 in their operations should also benefit in their innovation performance, because of their improved, leaner and so more suitable processes (Benner and Tushman, 2002; Lee et al., 2019). Atuahene-Gima and Murray (2007) suggested that, when companies increase their exploitation capabilities, their learning processes become more efficient, and this has a positive influence on their innovation performance. On the basis of these ideas, H4 was developed as follows:

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

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

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

Ardito et al. (2018) conducted one of the first attempts to test the link between process innovation and ambidexterity performance empirically. They demonstrated that process innovation (in production or IT processes) could increase the ambidexterity performance of a company. Here, we would like to study the opposite relationship, i.e. the effects of ambidexterity on overall innovation performance. In particular, we will consider the structural dimension of ambidexterity, whereby the Operations and Innovation departments are separate and distinct units in an enterprise. Operations should be directed towards exploitation, and innovation (R&D) towards exploration. This hypothesis is rooted in the idea that, by balancing exploitation and exploration, a company's 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 by pursuing exploitation and exploration alike. Conversely, other authors, such as Atuahene-Gima (2005), have shown that ambidexterity has a negative influence on innovation performance, and argue it is more suited to coupling high (low) exploitation with low (high) exploration, as a high-high pairing could lead to tension caused by the opposing pull of the two processes. However, as most of the authors, we have assumed that structural ambidexterity has a positive influence on innovation performance, therefore:

H6. Structural ambidexterity in a manufacturing 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 CINet Survey, a global research project carried out within the *Continuous Innovation Network* (CINet)[1]. A common questionnaire was administered between November 2016 and June 2017 in 11 countries (Austria, Brazil, Canada, Denmark, Hungary, Netherlands, Pakistan, Spain, Sweden and Switzerland) by local research groups under our coordination.

The sample frame used in each country restricted the survey to employees whose job title was chief operating officer or chief technology officer. According to previous research (e.g. Adebanjo et al., 2018), these are the officials within manufacturing firms who have the most knowledge of the topics under examination. In every country, where only one or neither of these positions were held in a company, we asked the chief executive officer to answer our questionnaire. Replicating Gastaldi et al. (2019), potential respondent bias was handled in two ways: (i) using scales derived from previous literature (see section 4.2), and whose effectiveness has already been verified in similar settings; (ii) pre-testing the questionnaire on practitioners and academics in the fields of the study, and revising it together, with the wording of some questions being modified on the basis of their feedback, before submitting the questionnaire to all potential respondents. These methodological choices meant that we also ensured methodological rigorousness and that the questions could be clearly understood by professionals.

The survey focused on respondents from manufacturing firms indexed in the International Standard Industrial Classification (ISIC) with codes ranging from 10 to 33 (similarly to Pramongkit et al., 2000). We contacted several manufacturing firms in each country and asked them to take part in the survey, working through the solid networks of local technical universities involved in the study. We endeavored to select a varied group of firms, in terms of size, focus and industries, replicating Kauppi et al. (2016). Questionnaires were distributed to the companies that agreed to take part; 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 entered into the global database. For early and late response bias tests, the coordinator for each country was required to compare the responses from early and late respondents (Armstrong and Overton, 1977). A t-test of difference was run on their sales figures, number of employees and ISIC code for early and late respondents, without finding any statistically significant differences. For the non-response bias test, each country coordinator compared the respondents with the non-respondents. A t-test of difference was run on their sales figures, number of employees and ISIC code. No statistical difference was found between the respondents and the non-respondents.

The potential common method bias was tested using the Harman single factor test. Less than 50% of the common variances were explained by one single factor, which indicates that the data gathered was not affected by problems of common method variance (Podsakoff et al., 2003). With multi-country data, measurement equivalence has also to be considered. In this case, calibration equivalence was ensured in the survey design by using standardized Likert scales items in all countries (Wiengarten et al., 2016). Translation equivalence was ensured by taking care that the translation guidelines were strictly followed in all countries. We assessed metric equivalence post-survey by calculating individual Cronbach's alphas for each country for all constructs, and individually each provided results above the threshold values.

4.2. Measures

We surveyed the literature to identify valid measures for related constructs and adapted existing scales to measure the different constructs mentioned in the theoretical background. 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 for 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 includes aspects related to new product development (Atuahene-Gima, 2005), employee skills (Pullman et al., 2009), project planning accuracy (Griffin and Page, 1993) and the capacity of launching environmental-friendly products (Wong et al., 1996). For each of these aspects, we asked the respondents

[1] For more information: www.continuous-innovation.net.

to think about their average performance over the past three years, and to relate it to their main competitors. This part was intended to reduce potential biases associated to idiosyncratic events.

Exploitation. A four-item scale (α = 0.83) was adapted from Atuahene-Gima (2005). All measures were assessed by asking participants to answer questions on their views about their Operations unit on a five-point Likert-type scale, ranging from “strongly disagree” to “strongly agree”. Table 1 gives the specific measures.

Exploration. A four-item scale (α = 0.73) was adapted from Akman and Yilmaz (2008). All measures were assessed by asking participants to answer questions on their views about their innovation department on a five-point Likert-type scale, ranging from “strongly disagree” to “strongly agree”. Table 1 gives 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 reaching a consensus. In order to overcome this issue, we are proposing an alternative way of operationalizing ambidexterity, which considers the combined dimension and the balance dimension simultaneously:

$$Ambidexterity = \frac{Combined\ dimension}{Balance\ dimension} = \frac{Exploitation + Exploration}{|\ Exploitation - Exploration\ |} \qquad (1)^{2}$$

In this computation, the value of the two approaches is summed and divided by the relative imbalance between the two strategies. As a consequence, the computation simultaneously addresses two different perspectives; on the one hand, the numerator is the sum of the exploitation and the exploration, which reflects how ambidexterity is calculated according to the combined dimension vision (Cao et al., 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 et al., 2009). Therefore, we were able to overcome the main drawbacks relating to summing or multiplying (i.e. difficulties in detecting the level of balance between the two strategies) and those relating to absolute difference (i.e. enterprises scoring low in both exploration and exploitation being considered as ambidextrous).

Investments in STs. A five–items scale (α = 0.74) was adapted from Vázquez-Bustelo et al. (2007) and Bottani (2010), asking respondents how extensively were STs being adopted and exploited within the respondent’s company. All measures were assessed by asking participants to answer questions on a five-point Likert-type scale, ranging from “not applied” to “high degree of application”. Table 1 gives the specific measures.

Business performance. Business performance was measured, as suggested by McDougall and Tyers (1994), through three items, where respondents were 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 – compared to that of their main competitors over the past three years. The focus on net profit, return on sales and profit growth ensures the comprehensive assessment of business performance.

Control variables. We controlled for three variables: region, industry and company size. The region variable was incorporated as 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 layered 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. The industry was coded through eight dummy variables corresponding to the industries of the various respondents (1 = food products manufacturing; 2 = rubber and plastic products manufacturing; 3 = fabricated metal products manufacturing, except machinery and equipment; 4 = computer, electronic and optical products manufacturing; 5 = electrical components manufacturing; 6 = machinery and equipment manufacturing; 7 = furniture manufacturing; 8 = others).

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[2] Whenever the value of the denominator becomes zero for any of the observations, the following formulae 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.

4.3. Data analyses

In order to answer our research questions, we conducted a three-step methodology. We first ran an exploratory factor analysis (EFR) to identify the underlying constructs. We then ran a confirmatory factor analysis (CFA) to test the distinctiveness of the constructs. Lastly, we used Structural Equation Modelling (SEM) to test the hypotheses and reveal the relationships between various constructs. All the analyses were conducted in Stata 14.

Concerning the data pre-processing, we first checked the responses to make sure that there were no outliers. Then, where more than 4 answers were missing (out of the 23 relevant questions), those responses were omitted from the analysis. Lastly, we conducted mean imputation for the remaining missing values. The final sample size after the data pre-processing contained 138 completed questionnaires.

We next conducted Principal Component Analysis (PCA) and, in order to choose the appropriate number of factors, we carried out 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 et al., 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 to be 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 presented in Figure 1. In addition, we have also given 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. CFI was considered to be 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 et al., 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 conducted an exploratory factor analysis including all 22 items corresponding to the 5 measures (business performance, STs, exploitation, exploration, innovation performance). This provides further evidence on the discriminant validity of the measures.

As mentioned, we used the KMO test to evaluate sampling adequacy. The smallest KMO measure is 0.69 (for two items only) while for most items the measure was greater than 0.75. The overall KMO for the complete model is 0.78. This indicates that the proportion of 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 carried out to detect the number of underlying factors. Figure 2 shows the scree plot and the results of the parallel analysis, indicating that a five factors model is the most appropriate, 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.

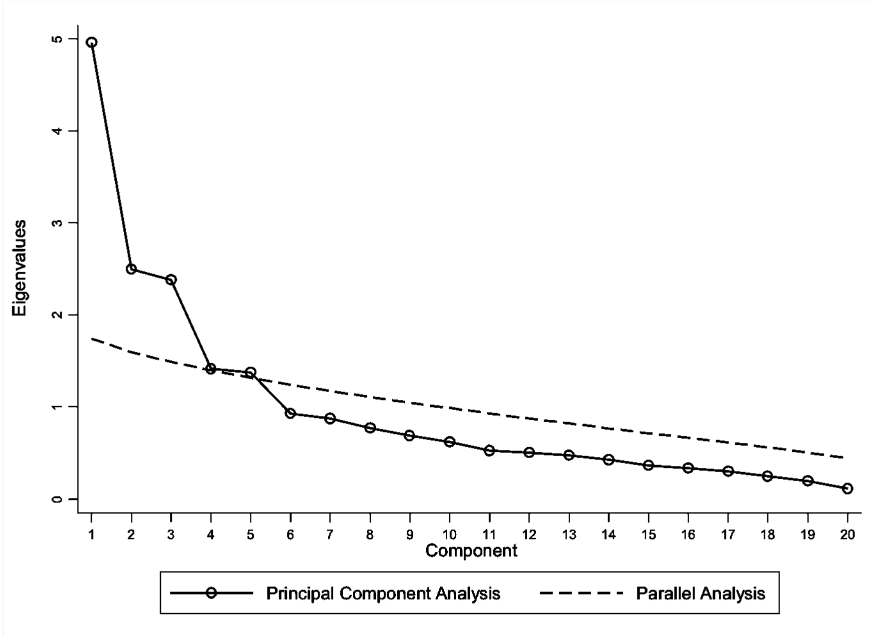

Figure 2. Scree plot of the results of parallel analysis with 1,000 repetitions

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***
Innovation performance	Total new product development costs as a percentage of sales	0.59	0.76
	Employee performance re 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	
Investment in STs	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 main competitor over the past three years	0.94	0.92
	Average performance, in terms of return on profit growth, relative to main competitor over the past three years	0.92	
	Average performance, in terms of return on sales, relative to 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 numbers of factors. In particular, we considered (a) a single factor model that incorporates all five constructs; (b) a two-factor model combining business performance and innovation performance (factor 1), exploration, exploitation and STs (factor 2); (c) a three-factor model combining business performance and innovation performance (factor 1), exploration and exploitation (factor 2) and STs (factor 3); (d) a four-factor model that combines innovation performance and business performance and, lastly, (e) a model that considers each construct as a separate factor. The fit indexes of the models are presented in Table 2 and confirm that the five 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*	*Investment in STs*
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	
Investment in STs	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 the exploration and the exploitation latent variables. This reduces the correlation between the ambidexterity measures and the exploration and exploitation latent variables, and hence mitigates the potential for multicollinearity between the variables. This approach is also used by Cao et al. (2009) for the combined dimension of ambidexterity. The correlation coefficients between the ambidexterity measure of Eq. 1 and the exploration and exploitation variables are 0.46 and 0.45, respectively. The correlation coefficients are below 0.5 and far smaller than the 0.65 threshold, which indicates potential for multicollinearity (Tabachnick et al., 2001).

5.3. Path analysis

Figure 3 shows 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).

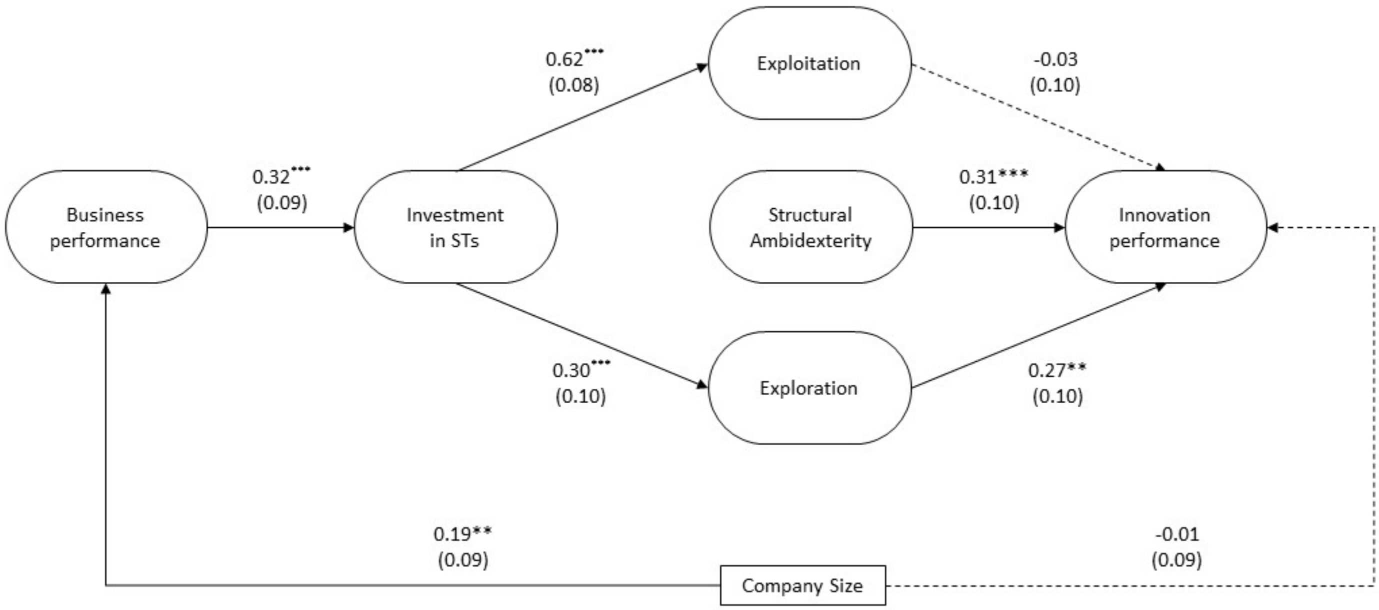

Figure 3. SEM results of the hypothesized model

Notes: the figure shows the standardized coefficients, 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*

The results indicate that business performance is positively related to STs (β = 0.32, $p < 0.01$). We found that STs significantly and positively affect both exploitation (β = 0.62, $p < 0.01$) and exploration (β = 30, $p < 0.01$). The model indicates that exploration is positively related to innovation performance (β = 0.27, $p < 0.05$), but that the effect of exploitation on innovation performance is insignificant (β = -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 (β = 0.31, $p < 0.01$). It is worth noting that the coefficient of ambidexterity is greater than the coefficient of the exploration construct (β = 0.31 for ambidexterity vs β = 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.

Concerning the control variables, company size has a significant effect on business performance (β = 0.19, $p < 0.05$), but an insignificant effect on innovation performance (β = -0.01). The coefficients of the dummy variable for South America on innovation performance is significant and negative (β = -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 for South America on business performance is negative and significant (β = -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 (β = -0.29, $p < 0.05$) when compared to Industry 1 (food products manufacturing, the reference category).

6. Discussion of the statistical results

On analyzing the numerical results above, it was possible to obtain several insights into the extant theory on ambidexterity and Industry 4.0. For the sake of clarity, in this discussion, we have considered the academic and managerial contributions separately.

6.1. Academic contributions

Focusing on the theoretical perspective, four main contributions can be highlighted. First of all, the outcomes of the statistical analyses highlight that Industry 4.0 positively affects the capability of simultaneously pursuing exploitation and exploration strategies within different departments (e.g. Operations department to "exploit", R&D department to "explore"), thus fostering structural ambidexterity within an organization. This finding is a remarkable contribution to the academic community because, as underlined in the literature review, there are virtually no papers that consider STs and ambidexterity simultaneously, and only a few articles have recently assessed the role of Industry 4.0 as an enabler for structural ambidexterity. Im and Rai (2014) discovered that information systems play a major role in enabling contextual ambidexterity, and they described how digital capabilities in inter-organizational relationship coordination can promote contextual ambidexterity. Park et al. (2020) recognized that digitization plays a greater role when pursuing the intrafirm pathway to achieve structural ambidexterity, but admit to a potential limitation in the generalizability of their findings to recent digital technologies. Our research is in fact the first empirical analysis to test this hypothesis in the intra-company context, thus filling a significant literature gap in the manufacturing domain (the gap in the literature actually refers to both services and manufacturing firms).

Secondly, the proposed model sheds light on the ambiguous relationship between structural ambidexterity and innovation performance. As stated in the literature review, many authors argue that, if a company aims to excel at both improving existing products and generating new ones, it should apply structural ambidexterity. It is also the case that no one has clearly demonstrated that structural separation positively influences overall innovation performance. Our analysis clarifies that, by pursuing structural ambidexterity, i.e. by combining exploitation within Operations and exploration within Innovation/R&D, companies can improve their innovation performance, thus filling another significant gap in the literature.

As third evidence, it has been demonstrated that good business performance can affect a company's ability to invest in innovation/R&D, and can lead to outstanding performance in innovation. As the literature analysis has shown, the positive effect of innovation on business performance has frequently been underlined, since an innovative mindset allows organizations to tackle environmental changes effectively and therefore improve their performance, creating a competitive advantage difficult to be matched by their competitors. However, it would appear that there are no works that cover the inverse relationship. In proving this positive connection, this research directly answers the question put forward by Piening and Salge (2015), who suggested investigating whether business performance has a positive influence on an enterprise's innovation performance. Additionally, the enabling role of monetary performance in the adoption of STs has been established, confirming that organizations which perform well are investing their resources into implementing these costly technologies. This fills another gap, since it advances the theory that well-performing companies could also be in a favorable position to face the Fourth Industrial Revolution.

Lastly, this paper is proposing an innovative way to operationalize ambidexterity in SEM path analysis. The review of the extant literature shows the lack of agreement between scholars regarding the conceiving of ambidexterity. Although there is broad consensus that ambidextrous organizations engage in both exploration and exploitation, it is unclear whether these firms concentrate their effort on the combined value of their work in exploitation and exploration, or on the value of their work in exploitation matching the value of their work in exploration. This paradoxical perspective refers to the dual theory of combined dimension and balance dimension, which has led several authors to calculate ambidexterity as the multiplication or the absolute difference between the two strategies/components. Nevertheless, as illustrated in the literature, both alternatives present serious drawbacks. The new formula proposed in this paper was found to be a reliable solution for preventing the dangerous issue of multicollinearity and for considering the two perspectives of combined dimension and balance dimension simultaneously.

6.2. Managerial contributions

Alongside its valuable academic implications, this study can provide useful managerial suggestions and thus support decision-makers in manufacturing firms.

The first and most important implication concerns fully embracing Industry 4.0 principles and, in particular, the adoption of STs as a reliable enabler of ambidexterity within a manufacturing context. This evidence, supported by the statistical analysis, implies that managers should opt for introducing new technological tools (e.g. industrial internet, additive manufacturing, RFId tags, etc.) as they will improve their company's capability to optimize and streamline its current production processes and, at the same time, enable it to explore new solutions that can give results in the long term. This is important, because researchers usually focus on the connection between investment in STs and related business performance (e.g. Dalenogare et al., 2018) and tend to ignore or underestimate the contribution of STs to innovation performance. As demonstrated by this study, STs can enable ambidexterity, and can thus have an impact in both the short term (business performance) and the long term (innovation performance). Therefore, both types of performance should be assessed through suitable KPIs and considering a wider range of strategic considerations rather than focusing only on efficiency gains, cost savings and short-term payback.

As a second practical implication, the study shifts the focus of the debate to the structural conception of ambidexterity. Managers should consider organizational separation as a viable solution for a company to become ambidextrous and, thus, to be aligned and efficient in its management of daily business as well as being adaptive to changes in the environment. In particular, this research suggests the companies should exploit cost saving measures in the production department and explore product and process redesign solutions in the R&D (product innovation / process innovation) department. In practical terms, this suggestion is in line with the model proposed in Tumino et al. (2017), according to whom data from digital devices in factories or connected products in the field can be used in operational efficiency projects (exploit) and also in new product or service design projects (explore), while also specifying that the two strategies should have specialized management, targets and KPIs. However, decision-makers should be careful, because separation must be correctly managed, otherwise it could lead to isolation, with innovative units too far away from the core business (O'Reilly and Tushman, 2008).

This study also emphasizes the fact that business performance can have a significant impact on the chance of ambidexterity projects being successful. Managers in well-performing enterprises – from a monetary point of view – should invest their finances in keeping up with the technological change that is taking place globally. In particular, given the high cost of introducing STS and their initial implementation, business performance (i.e. financial availability) constitutes a key condition of any I4.0 initiative. In this regard, in many regions worldwide, governments have launched national programs supporting digital transformation in their manufacturing sector. Backed by public money to underpin their investment plans, many companies have started out on their ST adoption process; nevertheless, public funding generally covers only a small part of the total monetary and organizational costs, and this kind of operation may soon backfire if companies are not prepared to back up their initial investment with suitable financial resources in the medium and long run. This finding has an additional implication for manufacturing firms, especially SMEs. The availability of financial resources is simply a necessary condition to invest in STs, management still has to decide whether to use those resources for such an investment, rather than just continuing along more traditional courses of action, such as investing in product innovation or improving/expanding their distribution channels. STs, as empirically proven in this paper, have the power to improve short-term and long-term performance simultaneously, therefore should be regarded as an extraordinary source of competitive advantage.

Lastly, interesting evidence for managers also stemmed from the analysis of the control variables. The SEM path analysis illustrates how the context in which organizations are operating has an influence over the possibility of achieving outstanding innovation performance. The level of innovation varies country by country, and this affects accessibility to STs. Therefore, in order to avoid wasting financial assets, decision-makers should evaluate the level of innovation for the industry in which the enterprise is operating. These results seem connected with the theory of industrial commons (Pisano and Shih, 2009), and the relevance of the geographical variable on the competitiveness of a company.

Lastly, as discussed in Section 4, the statistical analyses reveal a null impact of the company size; this means that STs are ambidexterity enablers both in small and large businesses. Once again, this is a strong message from a managerial viewpoint, as small businesses are usually deemed to be less capable of handling and leveraging on complex technological investment. Financial assets, instead, naturally in shorter supply within SMEs in absolute terms, are a stronger explanation for successful ambidexterity.

All in all, these considerations highlight the role of managers, the decisions they make and the organizational culture they create, as these factors are what really drives the practice of ambidextrous production innovation, while STs can act as its enablers.

7. Conclusions

In this study, we have shed light on how the transition to Industry 4.0 carried out through the adoption of STs could be an enabler of structural ambidexterity. The results demonstrate (i) the antecedent role of STs on ambidexterity at the intra-company level; (ii) how well-performing companies are currently investing in STs and thus are in a favorable position to improve their performance and (iii) how exploitation, exploration and structural ambidexterity enhance innovation performance in manufacturing firms in both the short and long term. These findings fill key gaps in current theoretical knowledge and have interesting practical implications.

There are some limitations that should be considered when interpreting the results of this research. The sample included incomplete responses (i.e. missing values) meaning that it was necessary to remove several observations where the values were lacking, which reduced the sample available to test the hypotheses. Moreover, the missing values were not distributed uniformly, as many missing values were from the same few countries. However, we conducted a data imputation analysis to avoid any substantial bias due to missing values. The questionnaire used to test our assumptions (i.e. the enabling role of STs over business performance and innovation performance) covered a given timeframe (i.e. the company's performance over the past three years), while it would have been better to measure a company's innovation performance for a longer period than that used for its business performance.

We envision several avenues for further investigation. Similar research could be conducted on a larger sample of countries, in order to gain a more comprehensive perspective on differences in performance. Moreover, using panel data to include the time lag between business performance and innovation performance could be an interesting path for future studies. Further analysis could also investigate other causal relationships, for instance, the direct path between STs and innovation performance or between STs and ambidexterity. It would be interesting to assess the impact of each single ST over structural ambidexterity and, thus, innovation performance. For instance, the effect of adopting additive manufacturing could be compared with the effect of implementing cloud manufacturing; by comparing the results, it would be possible to understand which ST is the most suitable, and in which scenario, to drive the simultaneous implementation of exploitation and exploration within the firm.

It is worth noting that the extant literature has often linked ambidexterity and company performance with environmental dynamism and market turbulence, investment volume with the management's level of risk aversion, and structural ambidexterity effectiveness with level of coordination within the organization. These relationships have not been considered in this study, but they could be included in the model with the purpose of gaining a more complete overview of company dynamics.

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