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Master of Science in Management Engineering

Companies' adoption of smart manufacturing technologies to achieve structural ambidexterity: an analysis with SEM

Master Thesis

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LIST OF ABBREVIATIONS

ABBREVIATION	MEANING
BD&IA	Big Data and Industrial Analytics
BP	Business Performance
CD	Coefficient of Determination
CINet	Continuous Innovation Network
COO	Chief Operating Officer
CTO	Chief Technology Officer
ERP	Enterprise Resource Planning
I4.0	Industry 4.0
ICT	Information and Communication Technology
IoT	Internet of Things
IP	Innovation Performance
OT	Operational Technology
RFId	Radio Frequency Identification
RMSEA	Root Mean Square Error of Approximation
SEM	Structural Equation Modelling
SME	Small and Medium Enterprise
SMT	Smart Manufacturing Technology
SRMR	Standardized Root Mean Square Residual

ABSTRACT

The opportunity of achieving long-term success and sustainable competitive advantage over competitors depends on a company's ability to exploit its current capabilities while simultaneously exploring fundamentally new competencies. The way of balancing these two strategies is defined as ambidexterity, which has emerged as a fundamental research stream in organization science to understand how firms can enhance their competitiveness.

In this context, scholars have deeply investigated how firm should proceed to achieve such equilibrium and, only recently, some researches have started focusing on the pivotal role that Information and Communication Technologies (ICTs) in general and Smart Manufacturing Technologies (SMTs) in particular can play as possible antecedents of ambidexterity. No empirical studies assess how companies can simultaneously improve their operations' exploitation and innovation' exploration orientations, and thus achieving structural ambidexterity, by implementing Smart Manufacturing Technologies (SMTs).

The study relies on Structural Equation Modelling (SEM) techniques to check if these relationships are positively supported, and if enterprises with good Business Performance (BP) are in favourable position to achieve better innovation results, leveraging on SMTs and structural ambidexterity as mediators. Beyond that, the proposed theoretical model also evaluates if well-performing organizations can easily invest in SMTs, and if operations' exploitation, innovation's exploration and structural ambidexterity positive influence Innovation Performance (IP).

All the hypotheses are supported by the statistical analyses, thus empirically demonstrating previously unexplored relationships – i.e. well-performing companies can easily invest in SMTs; positive influence of SMTs adoption over operations' exploitation and innovation's exploration – and clarifying unclear connections which causes conflicts in the extant literature – i.e. positive influence of exploitation, exploration and structural ambidexterity on IP.

As a result, this research provides relevant implications for the scientific literature and for practitioners.

Keywords: Structural Ambidexterity, Exploitation, Exploration, Industry 4.0, Smart Manufacturing Technologies, Innovation Performance.

0. EXECUTIVE SUMMARY

Nowadays companies are facing a complex, highly competitive and rapidly changing environment, characterized by the presence of continuous technological innovation. As a reflection of the new environment, firms need to be competitive both in the short and in the long-term, and to increase their competitiveness by implementing technological innovation.

In order to survive in this context and to accomplish this challenging objective, firms should be ambidextrous. This term has been introduced by Duncan (1976) and, starting from the nineties, has been deeply investigated by scholars. In 1991, March proposed the terms exploitation and exploration to identify the two divergent strategies constituting ambidexterity, meaning that companies should balance exploitation in existing knowledge domains and exploration in the novel ones. Since that moment, several definitions of ambidexterity have been developed, and scholars have identified four main solutions to handle the trade-off between exploration and exploitation: temporal separation, which alternates during time exploitation and exploration; structural ambidexterity, which performs the two strategies in different units of the organization; domain separation, which addresses the strategies in two different domains; contextual ambidexterity, which pursues ambidexterity by leveraging on individuals' abilities to shift their mindsets.

Despite the absence of consensus in the extant literature, a remarkable and accepted definition of ambidexterity is the one proposed by O'Reilly and Tushman (2013, p. 324), who define it as ''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 to also compete in new technologies and markets where flexibility, autonomy, and experimentation are needed''.

Beyond that, another relevant trend is gaining interest and curiosity between scholars: Industry 4.0 (I4.0). This concept was firstly introduced in Germany in 2011, and refers to the challenging objective of connecting digital and physical world in order to help enterprises to better run their businesses; indeed, by adopting some Smart Manufacturing Technologies (SMTs), the organization would be able to achieve remarkable results both in the short-term, by optimizing the current procedures, and in the long-term, by collecting and handling an enormous amount of data to predict future trends.

In detail, the SMTs aim at merging the Information and Communication Technology (ICT) and Operational Technology (OT) worlds by leveraging on new smart connected objects that collect data from the real world and integrate them with the enterprises' systems.

Even if I4.0 comprehends several technologies, the extant literature generally agrees in considering Internet of Things (IoT), Big Data and Industrial Analytics (BD&IA) and cloud manufacturing as the leading actors (Lu, 2017). However, in this research also other relevant innovations are assessed – i.e. additive manufacturing, Enterprise Resource Planning (ERP) and computer-aided process planning.

The two illustrated topics – i.e. ambidexterity and I4.0 – represented the target of the literature review phase, which helped to define the state-of-art of the scientific literature related to these aspects. In detail, the analysis started by investigating researches concerning ambidexterity and its two enablers – i.e. exploitation and exploitation –, in order to identify all the possible ambidexterity configurations, its antecedents, its effects and how to operationalize it in statistical analyses. Afterwards, the focus shifted on I4.0, with the objective of giving a general overview of this topic and its enabling technologies – i.e. SMTs -, thus illustrating their impacts and barriers to the implementation.

As a result, the following remarkable gaps emerged:

I. Even if the impact of I4.0 over Business Performance (BP) is widely investigated (Dalenogare, Benitez, Ayala and Frank, 2018), the inverse relationship – i.e. the enabling effect of good monetary performance over SMTs' adoption – is not deeply evaluated;
II. Many scholars have examined and clearly demonstrated the positive influence of ambidexterity over Innovation Performance (IP); however, the extant literature mainly focuses on the contextual configuration of ambidexterity or describes it as a generic balance between exploitation and exploration. Therefore, the lack of studies evaluating the relationship between the structural configuration of ambidexterity and IP is an important gap that must be filled;
III. Even if several researches address ICTs' impact on company's business, only two papers directly refer to SMTs' influence over ambidexterity level: a case study developed by Gastaldi, Appio, Corso and Pistorio (2018) and an empirical research at the interorganizational context developed by Im and Rai (2013). Therefore, no empirical studies simultaneously consider SMTs and ambidexterity at the organizational level.

Considering the literature review and the relative gaps, three research questions that this thesis aims at solving have been defined:

I. Do SMTs allow company to be ambidextrous, and thus pursue at the same time exploitative and explorative strategies?

II. Do exploitation, exploration and structural ambidexterity have a positive impact on IP?

III. Are well-performing companies, from a financial perspective, in a good position to have greater IP?

The third question is a direct consequence of the study conducted by Piening and Salge (2015), which prove the positive influence of IP on BP, supposing that inverse relationship equally holds true and thus should be investigated by future researches.

In order to deal with these questions, the conducted study relied on a research framework that entailed the development of a theoretical model to address and answer to these questions, the collection of the proper data, the preparation of the dataset to guarantee the results quality and, finally, the statistical analyses to provide insights based on empirical evidences.

Accordingly, Figure 1 and Table 1 illustrate the hypotheses tested in the conducted work and the definition of the constructs constituting the model in order to ease the interpretation of the theory which underlies the conducted study.

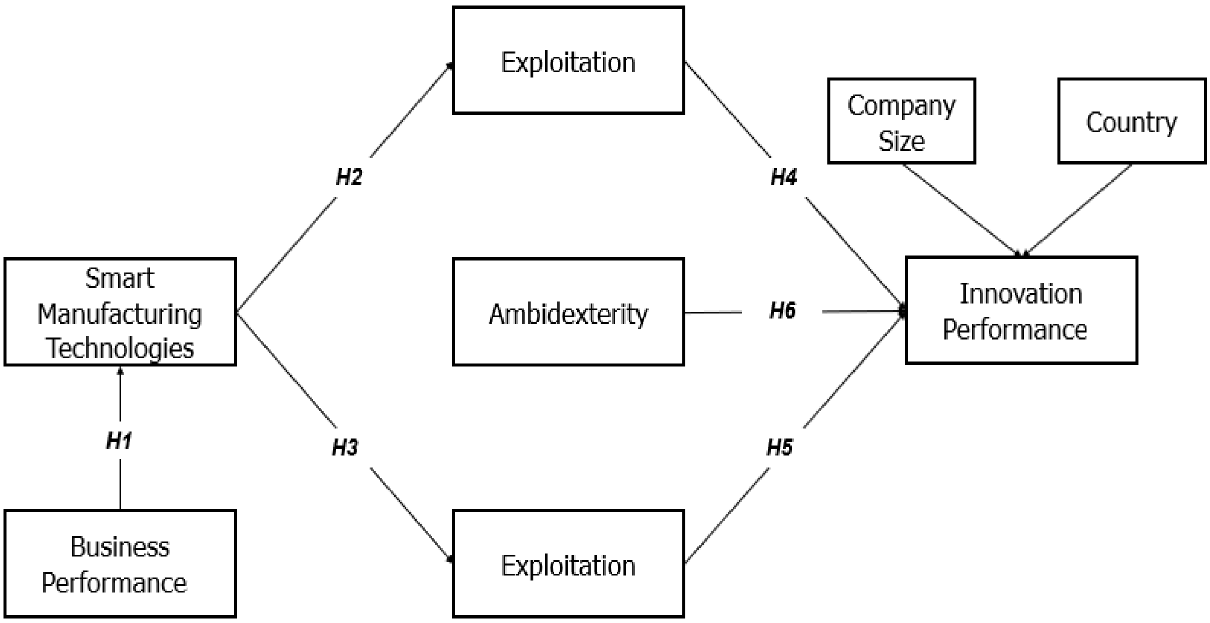

Figure 1: Theoretical model proposed by this research

CONSTRUCT NAME	DEFINITION
Business Performance	The financial performance of the company compared to competitors' ones
Smart Manufacturing Technologies	The level of adoption of SMTs within the company
Exploitation	The operations' exploitation level within the company, assessing the processes adopted within the production function
Exploration	The innovation' exploration level within the company, assessing the processes implemented within the innovation function
Ambidexterity	The ability to pursue, at the same time, operations' exploitation and innovations' exploration, thus investigating how much the company is structurally ambidextrous
Innovation Performance	The innovation level of the company compared to competitors' ones

Table 1: Definition of the constructs

First of all, the proposed model aims at verifying if companies with good BP can easily embrace I4.0, since SMTs are costly and require high investments (H1). Afterwards, it evaluates if firms which are currently employing SMTs are in a favourable position to exploit within their operations (H2) and explore within the innovation function (H3). The underlying principle is that I4.0's introduction should directly influence operations' exploitation, since SMTs lead to the optimization of the time-cost trade-off, reducing resource utilization and thus allowing to focus the production processes on the refinement and extension of existing competences and technologies – i.e. the exploitation's essence. Beyond that, implementing SMTs allows also to revolutionize the way data are collected, since smart objects extract an enormous quantity of information that can be used to develop new knowledge and seize the possibility to shift to new technological trajectories – i.e. being explorative.

Finally, the model wants to clarify the impacts of exploitation, exploration and ambidexterity over the IP, both in the short and in the long-term. The extant literature highlighted how generally scholars link exploitation with brilliant performance in the short-term, whereas exploration supports more the results in the long-term; however, the effects of both these two strategies over the general IP is not clear, since contradictory insights are provided. Similarly, there is no consensus on how ambidexterity influences IP: even if researchers generally agree in arguing that firms should be competitive both with existing and emerging trends, some authors demonstrate diminishing performance due to difficulties in managing such different strategies. Therefore, this study evaluates if organizations focused just on operations' exploitation (H4), just on exploration within the innovation function (H5), or the ones able to combine these two aspects with structural ambidexterity (H6) are in a favourable position to enhance their IP. Additionally, the influence of firms' country of origin and size over such performance is verified by means of control variables. The selection of these two variables is a direct consequence of the literature review process and aims at increasing the accuracy of the statistical analyses.

Once established the theoretical model, the software Stata has been exploited to practically generate and analyse it.

In order to accomplish this objective, an accurate and proper data source was necessary. In particular, this study reaped the benefits of a survey emitted in 2016 within the Continuous Innovation Network (CINet) with the aim of analysing the performance of manufacturing companies. The target sample were the Chief Operating Officers (COOs) and the Chief Technology Officers (CTOs) of 370 enterprises located in eleven distinct countries and operating in several different industries – e.g. automotive, apparel, food, beverage, etc. In detail, the two managers have been asked different questions, according to the department which they were operating in.

Since this thesis investigates exploitation in the production domain and exploration in the technological one, both the production and the new product development sections of the survey were necessary to carry on a precise and correct analysis. As a consequence, only the companies that effectively answered to all the five sections have been taken into considerations – i.e. both the COO and the CTO filled in the survey; in doing that, enterprises coming from two of the eleven countries have been excluded from the analysis, since no one of them answered to all the sections of the survey.

This database has been subsequently prepared in order to guarantee the quality of the statistical analyses. First of all, a reduction of the available variables has been carried out since, by digging into the extant literature, it emerged that only a few sets of them could be deemed adequate to generate the constructs of the theoretical model. Therefore, questions which has been deemed not useful to represent the constructs have been immediately excluded to slim down the data matrix and thus speed up the subsequent phases.

Afterwards, the obtained database has been cleaned, by eliminating observations and answers comprehending incomplete data – i.e. missing values – and noise data – i.e. outliers-, which may generate inaccuracies.

Finally, a set of dummy variables has been included to represent the control variables related to country and company size. As a result, the final dataset was made up by 140 observations and 29 variables.

Once carried out these adjustments, the focus shifted on how generating the constructs that constituted the proposed theoretical model. In order to do that, two techniques have been exploited: exploratory factor analysis, which reduced the dimensionality of the dataset by creating factors as linear combination of the input variables, and Cronbach's alpha, which validated the items' assignment to each factor by assessing internal consistency of the retained factors.

A different procedure has been followed to operationalize the ambidexterity construct.

The analysis of the literature illustrated the absence of a general consensus regarding how to express this interaction: several authors model it according to the combined dimension perspective, which states that each strategy could help in leveraging the effect of the other, and resources can be simultaneously deployed in both approaches; others opt for the balance dimension perspective, which affirms that exploitation and exploration should be in equilibrium, in order to mitigate the risk associated to becoming obsolescent or managing too much novelty and knowledge. In practice, the combined theory operationalizes ambidexterity as the multiplication or the sum between the two approaches, whereas the balance one as the absolute difference. This work, in order to solve the conflict and the limitations of each perspective, proposes a new formula to compute ambidexterity which allows to simultaneously consider the combined and balance dimensions:

$$Ambidexterity = \frac{(Exploitation^{+} + Exploration^{+})}{|Exploitation - Exploration| + 1}$$

The numerator includes the absolute magnitude of each independent approach, whereas the denominator reflects the relative distance between them. Therefore, this method is complete from a theoretical point of view.

Beyond that, two adaptions have been applied to refine the formula: concerning the numerator, given the normalization procedure automatically carried out by Stata, the values of exploitation and exploration have been rescaled so that ambidexterity had positive scores, in order to avoid issues related to sum between negative numbers; afterwards, a constant value has been added to the absolute difference to prevent the possibility of having a null denominator. In particular, this parameter has been assigned a value of 1 since, in case exploitation and exploration's scores were equal, by setting at 1 the denominator, the level of ambidexterity would just depend on the numerator – i.e. the combined dimension.

Once all the constructs have been generated and validated, the data analysis phase ended with the implementation of the Structural Equation Modelling (SEM) technique, which leveraged on the obtained factors as input variables to test the theoretical model. Thanks to this procedure, all the relationships between constructs and items of the proposed model have been assessed and evaluated: as result, the statistical analysis provided the standardized path coefficients, which reflect the intensity of the relationships, and the p-values, which express the significance level of the relationships. In practice, the maximum likelihood technique has been carried out without including missing values, given the high number and non-random pattern of empty values. As a consequence, the number of observations available to test the model drop to 62. Figure 2, Table 2 and Table 3 illustrate the detailed outcomes of the analysis.

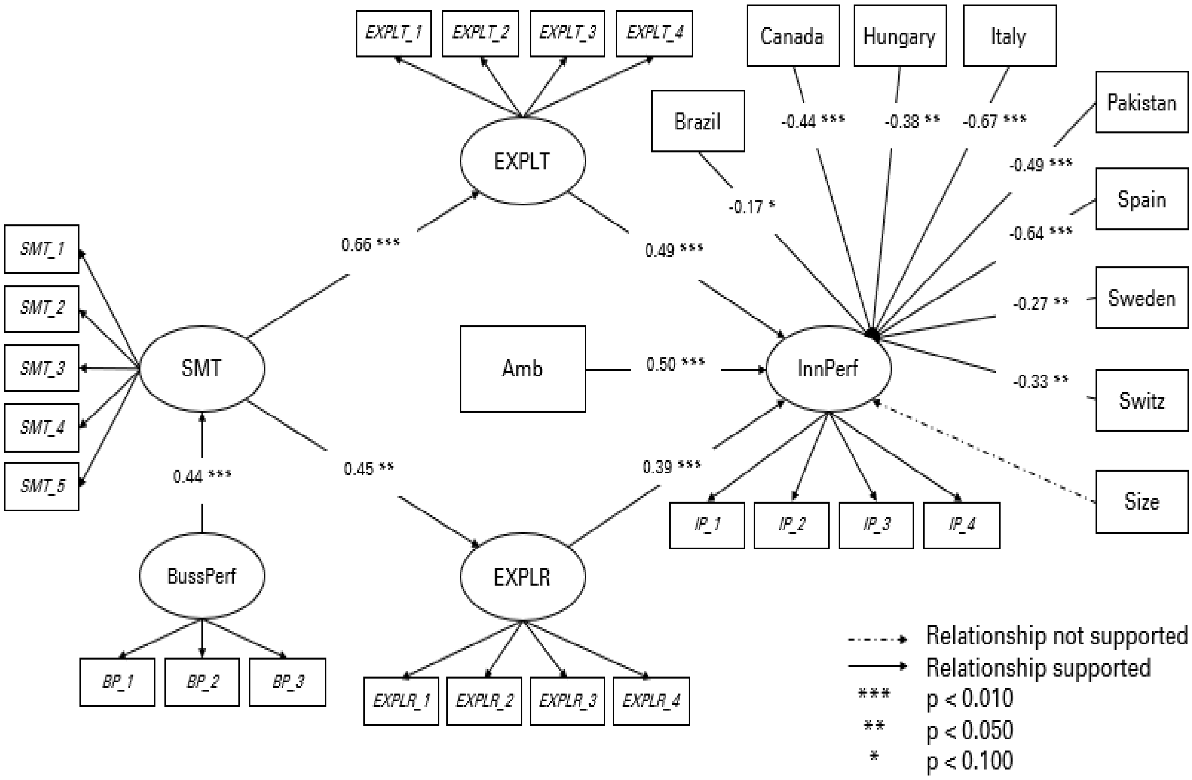

Figure 2: Results of the SEM path analysis

HYPOTHESIS	STD PATH COEFFICIENT	P VALUE	STATISTICAL VALIDITY	RELIABILITY
BP → SMT	0.44	0.005	Supported	Strong
SMT → Exploitation	0.66	0.001	Supported	Strong
SMT → Exploration	0.45	0.010	Supported	Medium
Exploitation → IP	0.49	0.000	Supported	Strong
Exploration → IP	0.39	0.001	Supported	Strong
Ambidexterity → IP	0.50	0.000	Supported	Strong

Table 2: Results of the hypotheses testing analysis

HYPOTHESIS	STD PATH COEFFICIENT	P VALUE	STATISTICAL VALIDITY	RELIABILITY
Company Size → IP	0.014	0.893	Not supported	-
Brazil → IP	- 0.17	0.074	Supported	Weak
Canada → IP	- 0.44	0.000	Supported	Strong
Hungary → IP	- 0.38	0.010	Supported	Medium
Italy → IP	- 0.67	0.000	Supported	Strong
Pakistan → IP	- 0.49	0.009	Supported	Strong
Spain → IP	- 0.64	0.001	Supported	Strong
Sweden → IP	- 0.27	0.018	Supported	Medium
Switzerland →IP	- 0.33	0.019	Supported	Medium

Table 3: Results of the control variables testing analysis

The SEM technique supported all the six hypotheses which underlie the model, thus answering to the three research questions addressed by the thesis. Therefore, the main outcome of the proposed model may be summarized as follows:

- Firms achieving outstanding results, from a financial viewpoint, are in a favourable position to enhance their IP;
- The embracement of I4.0 within the company is an enabler of ambidexterity, since the implementation of some SMTs positively affects exploitation and exploration at the same time.
- Structural ambidexterity, meant as exploiting within the operations department and exploring within the innovation one, is a reliable mediator of the path between BP and IP;

In conclusion, this study provides several contributions to the academic literature:

- This research is the first empirical analysis which evaluates the enabling role of SMTs implementation over structural ambidexterity in the intra-company context, thus filling a significant literature gap. Consequently, firms should opt for introducing new technological tools which will improve the capability of the firm to optimize and standardize the actual production’s processes, achieving higher efficiency in handling the already developed knowledge, and simultaneously explore new solution by collecting more data and using them to predict future trends;
- The proposed model confirms the theory of positive impact of exploitation and exploration over IP. Indeed, by focusing on exploitation activities within the operations’ department or

on exploration within the innovation one, firms would be able to enhance their IP. If correctly managed, these two strategies will not lead to the drawbacks hypothesized by the extant literature: rigidity related to high degrees of operations' exploitation, difficulties in managing too much novelty as a consequence of too much exploration within the innovation function. Additionally, it is certified the positive influence of structural ambidexterity over IP, since the proposed configuration recognizes the differences and tensions existing between the two approaches, and separates them into two independent departments of the company;

- By leveraging on the mediating role of SMTs and structural ambidexterity, the conducted study proves the positive impact of obtaining good BP over the capability of being innovate, thus directly answering to the question proposed by Piening and Salge (2015);
- The enabling role of monetary performance over SMTs' adoption is certified, thus proving that organizations should perform well in order to adopt such costly technologies;
- In generating the model for the statistical analyses, this research has developed a new way to operationalize the ambidexterity construct, which simultaneously includes the combined and balance dimensions. Therefore, a possible way to solve the conflict regarding how operationalising the interaction between exploitative and explorative is provided to scholars.

The aforementioned theoretical contributions can be converted into useful suggestions to support the decision-makers of enterprises. Top managers of well-performing companies should invest money in SMTs, since such technologies allows to simultaneously pursue exploitation and explorations strategies. Additionally, they should consider the organizational separation as a reliable and practicable way to be ambidextrous and, thus, achieve outstanding IP.

In conclusion, the main limitation of this thesis consists in the dimension of the sample which has been adopted for the empirical testing. Although the dimension of the dataset was sufficient to ensure the accuracy of the performed analyses, future research should seek to overcome the data availability issue to improve the quality of the study. Beyond that, it would be also interesting to address the contribute of each single SMT in enhancing ambidexterity.

1. INTRODUCTION

1.1 Research Context and Objectives

The dynamic and continuously changing environment is forcing companies to quickly react to complex and significant challenges. Meanwhile, it is also necessary to continue improving and optimizing the already implemented procedures.

This twofold objective is at the heart of ambidexterity, which is defined as the organization's ability to be efficient in the management of today's business and also adaptable for coping with tomorrow's changing demand (Tushman and O'Reilly, 1996), thus requiring to use both exploration and exploitation techniques to be successful. In the last years, the extant literature has exponentially increased the number of studies that examine ambidexterity within different industries – e.g. Banks, Healthcare, Aerospace, etc. -, different fields– e.g. supply chain management, customer management, new product development, etc. – and considering several possible antecedents – e.g. formal planning, environmental dynamism, organizational structures and context, etc.

Nevertheless, there is no general consensus about ambidexterity effects, as some studies associate it with diminishing returns. Consequently, it is interesting to understand how enterprises should face this remarkable topic and if the opportunity of achieving a competitive advantage over competitors would be obtained.

This theme could be easily intertwined with another significant and current trend: Industry 4.0 (I4.0). The latest breakthrough innovations are entering the manufacturing world and strongly influencing the way in which enterprises should manage their businesses. McKinsey (2015) clearly illustrates how not only the structure of the organizations but also the competitive market is changing; hence, decision-makers of companies must react to keep up with these advancements without neglecting the entrance of new competitors or the advent of new actors – e.g. the suppliers of Information and Communication Technologies (ICTs). The embracement of I4.0 practically consists in implementing the Smart Manufacturing Technologies (SMTs), which can bring significant benefits to the firms. The crucial role of such technologies is underlined also by some managers of well-known enterprises. For instance, the Head of Corporate Function Technology, Innovation and Sustainability at ThyssenKrupp Corporation affirmed that "Industry 4.0 will impact the whole product lifecycle end to end – from design to production, the actual usage phase until end-of-life – and cannot be attributed to one single department of the firm. The digital transformation is a cross-functional effort that needs to be addressed by the whole company".

By simultaneously approaching the two aforementioned topics, the conducted research aims at analysing how companies with good financial performance could easier invest to adopt SMTs. Once implemented such technologies, organizations may leverage on them to be in a favourable position to achieve structural ambidexterity, which consists in establishing separated departments to independently pursue exploitation and exploration strategies; in particular, the conducted research proposes to exploit within the production department and to explore within the innovation one. The correlation between SMTs' implementation and level of ambidexterity achieved lies in the possibility to enable a more flexible and automatic production, in order to cover both high volumes and high variety of demand by embracing I4.0 and properly managing an enormous amount of data. Beyond that, also the impact of being simultaneously exploitative and explorative over the Innovation Performance (IP) obtained by enterprises is assessed.

1.2 Thesis Contributions

The performed study, by carrying out robust statistical analyses, seeks to fulfil the previously mentioned goals; this provides significant contributions to both academic scientific literature and decision-makers of a company.

The research firstly aims at clarifying the existing conflict regarding how to achieve ambidexterity, by showing how the structural separation could lead to remarkable improvements of the achievable performance. As a consequence, decision-makers should follow this strategy and, thus, establish two separated functions: one dedicated to exploiting the current operations procedures, the other to exploring innovative processes.

The thesis also tries to provide theoretical implications with respect to the almost completely unexplored relationship between I4.0 and structural ambidexterity. Going into detail, the enabling role of SMTs over exploiting the operations and exploring the innovation is evaluated. In the same way, also the impact of having good monetary performance over SMTs' adoption is assessed, with the aim of proving that organizations should perform well in order to be able to adopt such costly technologies. From this, the research also seeks to demonstrate the indirect impact of good financial performance over the ability to achieve outstanding IP, which has not been examined in the past. Therefore, managers may be encouraged to invest money in SMTs, since this strategical choice may put the organization in a favourable position to realize structural ambidexterity and thus enhance IP.

Finally, this research also aims at solving an existing conflict regarding how to model ambidexterity in statistical analysis, by proposing an innovative formula to operationalize the interaction between exploitation and exploration strategies.

1.3 Structure of the Thesis

The research has been divided into six different chapters.

Chapter 1 has introduced the context of the study, with the objective of illustrating some goals that it aims at realizing; afterwards, the possible theoretical and managerial contributions for scholars and decision-makers have been presented.

Chapter 2 describes the main findings originated by examining the extant literature. The first part assesses all the possible ambidexterity configurations and how to realize them; the second one describes the interesting topic of I4.0, showing the possible impacts and challenges stemming from the implementation of SMTs. The chapter ends by listing all the gaps emerged from this analysis.

Chapter 3 leverage on the literature gaps to formulate the research questions which the thesis aims at answering. Afterwards, the chapter illustrates the methodology adopted to perform the analysis of the literature and to generate the theoretical model which underpins the study, alongside with the research hypotheses. All the subsequent sections are dedicated to explaining the procedures implemented and the statistical techniques exploited to demonstrate such hypotheses and, thus, satisfying the research questions.

Chapter 4 illustrates the outcomes of the statistical examination to express whether the hypotheses have been confirmed or denied, without providing an interpretation.

Chapter 5 seeks to discuss and clarify such results from a theoretical viewpoint. The goal is to connect the outcomes to the already existing literature in order to draft observations and extrapolate useful insights.

Chapter 6 includes the contributions provided to academic scholars and decision-makers. The thesis ends by illustrating the shortcomings of the study and the possible further researches stemming from them.

2. LITERATURE REVIEW

This chapter has the purpose to provide, through a revision of the extant literature, a clear overview of the state-of-art of the main topics addressed in this work. In particular, the focus is centred over a crucial theme: ambidexterity. Beyond that, I4.0 is addressed as possible enabler that companies can adopt in order to be ambidextrous.

In practice, the chapter is divided into four sections: (i) the examination of the two divergent activities that must be combined in order to be ambidextrous – i.e. exploitation and exploration; (ii) the direct assessment of ambidexterity, the underpinning principle of this thesis, seeking to identify a precise definition of the concept, how to achieve it, the benefits it entails, its existing antecedents and how to operationalize it in Structural Equation Modelling (SEM); (iii) the illustration of the state-of-art of I4.0 and SMTs, considering the basilar concepts and definitions, the enabling factors, the benefits and the barriers to the implementation and (iv) the summary of the findings provided by the extant literature and the gaps identification. The final phase has a great relevance since it paves the way for the definition of the research questions, which are formulated in sub-section 3.1.1.

2.1 Exploitation and Exploration

The starting point of the analysis is the famous article by March (1991), one of the first in which exploration and exploration are taken into account together, and their relationship analysed. From that moment, since they have opposite meaning, these two concepts are often considered as two sides of the same coin, usually generating a trade-off between them; however, at the same time, they should be closely related, as it is explained and underlined in the ambidexterity section.

According to March (1991), the exploitation's essence is the refinement and extension of existing competences and technologies, usually leading to predictable and positive returns; on the other hand, the exploration's gist is about the experimentation and the searching of new knowledge, obviously leading to more uncertain and distant, in terms of time, results.

This idea is supported by He and Wong (2004), who demonstrate how firms specialized in exploratory strategy show larger variation in performance, relative to their mean values, than enterprises that are focused on exploitative strategy. Levinthal and March (1993) provide with a more precise definition of the concepts, connecting the two notions only to the knowledge domain, in which exploitation and exploration correspond to the use and refinement of already existing knowledge versus development of new one.

A key aspect when defining exploitation and exploration is the viewpoint taken, because they are investigated at various levels of analysis, generating researches at the individual, group, organizational, inter-organizational and industry levels (Lavie, Stettner and Tushman, 2010). Going more in dept, and starting from the individual level, exploitation is defined as behaviour that make optimal performance in one task (Aston-Jones and Cohen, 2005) which, looking at the organizational level, becomes the tendency to transform reliable behaviours into routines (Harry and Schroeder, 2000). On the contrary, exploration, at the individual level, can be defined as the behaviour leading to "disengagement from the current task and the search for alternative behaviours" (Aston-Jones and Cohen, 2005, p. 430). This definition reflects the idea of exploration that, at the organizational level, becomes the continuous search for new opportunities, and the regular experiment of new ideas (Miles and Snow, 1978).

The definition changes also from one company to another: according to Lavie et al. (2010, p. 115), "certain knowledge, technology, or markets may be new to one organization but familiar to another. Consequently, one organization's exploration may be considered exploitation by another." Gupta, Smitha and Shalley (2006) support this view, highlighting the need to clearly specify the peculiar unit of analysis when talking about the topic.

In this research, the two concepts are analysed mainly at organizational level, the most studied one. From this perspective, one of the most important interpretation is the one by Atuahene-Gima (2005), who states that exploitation aims at greater efficiency and reliability of existing innovation activities, whereas exploration has the objective of attaining flexibility and novelty in product innovation through increased variation and experimentation. Exploitation has the intent to answer to actual environmental condition, by adapting the existing competencies to the needs of existing customers (Harry and Schroeder, 2000); exploration is expected to drive latent environmental trends by creating innovative technologies and new markets (Lubatkin, Simsek, Ling and Veiga, 2006).

He and Wong (2004, p. 483-484) follows this idea and define exploitation as "technological innovation activities aimed at improving existing product-market domains" and exploration as "technological innovation aimed at entering new product-market positions".

Another interesting aspect is the one captured by Jansen, Vera and Crossan (2009), who associate the two concepts to the different leadership style, demonstrating that transactional leadership is associated with exploitative innovations, while transformational leadership is associated with exploratory ones. This association makes sense, since the leadership style reflects the nature of the dimensions: exploitation is linked to transactional behaviours, characterized by supporting the improvement and refinement of existing competences;

exploration is linked to the transformational leaders who inspire organization to challenge institutionalized learning and out-of-the-box thinking processes.

According to Benner and Tushman (2002), exploitation regards improvements in existing components, remaining on the same technological trajectory, whereas exploration require a shift to a new technological trajectory.

These definitions follow the first stream of study that support the idea that both concepts are characterised by the presence of some type of learning. In contrast, there is a second approach which differentiate the two constructs according to the absence or presence of learning, defining exploitation as all the activities associated with past and already existing knowledge, and exploration as all the activities related to any kind of learning and innovation (Rosenkopf and Nerkar, 2001). This second view is at odds with March's definition (1991) and with Gupta et al. (2006), who conclude that in both the dimensions some type of learning is present. Once established that learning is present both in exploitation and exploration, it is important distinguishing the type of learning that differentiate these concepts.

According to Wooldridge and Floyd (1989), exploitation is characterized by a top-down learning process, in which the senior management aims at systematizing the routines and behaviours to refine current competencies; differently, exploration is usually defined by a bottom-up process, in which the middle managers promote the renewal of old routines in favour of a new course of action. This is one of the aspects that highlights the diametrically opposed and conflicting nature of these activities, which derives also from other several issues, like the initial decision on resource's allocation and the following expected outcomes.

From this viewpoint, it is clear that exploitation and exploration are mostly incompatible and contradictory: they are characterised by opposite managerial behaviours and routine since they compete for scarce resources and, thus, generate tensions (He and Wong, 2004).

These differences are reflected also in the organizational structure that companies design to pursue one dimension or the other. In particular, Bruns and Stalker (1961) distinguish between mechanistic and organic structures: a mechanistic structure perfectly fit with exploitation, since an exploitative approach aims at increasing stability and efficiency (Lewin, Long and Carroll, 1999), pursuing incremental innovation and creating organizational structures characterized by centralized and hierarchical structures that usually lead to organizational inertia; on the contrary, the organic one is more suitable for exploration, since focusing on exploration means being flexible and open to change (Lewin et al., 1999), because companies try to pursue more radical innovations, which requires high experimentation level with less certain returns in the short-term (Popadiuk, 2012). This mindset leads obviously to organic, decentralized and flat structures, which require a high need of inter functional coordination, since the higher risk related to their innovation path implies the necessity to facilitate communication; in contrast, a firm pursuing exploitation does not necessarily require high coordination (Atuahene-Gima, 2005).

The different structure implies also different consequences for companies in the future, with exploitative enterprises that face the threat to become outdated, since they focus themselves on refinement of existing technologies competencies without developing new solutions (Holmqvist, 2004). Also, according to Popadiuk (2012), during exploitation less effort and budget are made available to revolutionary innovation and, in the long-term, this could lead to knowledge's obsolescence, due to difficulties in adoption of new directions, according to rigidity problems and an organizational inertia. By contrast, explorative companies sacrifice short-term productivity to achieve long-term innovation supported by new knowledge (March, 1991), with the aim of reaching higher return in the future, thus needing to be flexible and open to change. That represents the capability-rigidity paradox, defined as the strategic dilemma of exploiting providing, through incremental innovation, short-term gains versus exploring and obtain long-term benefits, through radical innovation. (Gupta et al., 2006).

Nevertheless, by focusing only on exploration, organizations might suffer few returns from the knowledge generated because, when an enterprise overemphasizes exploration and exclude exploitation, it increases exponentially the possibility of failing to appropriate returns from its costly search activities (Cao, Gedajlovic, and Zhang, 2009). In this case, companies suffer a high risk to enter into a dynamic unrewarding cycle of failures, defined as "failure trap" by Levinthal and March (1993). Both exploitation and exploration are iteratively self-reinforcing, as every time an organization fails in its exploration path, it starts again with more search, continuously replacing ideas with new ones, but always achieving failure. This because, at a certain time, firms should stop looking at the long-term and should improve their efficiency in order to be competitive on the market, since the return from any particular innovation is function of the company's experience with it. The same concept can be translated to exploitation with the "success trap", a cycle in which exploitation often leads to success reinforcing further exploitation along the same trajectory. This cycle is very risky because it strengthens organizational inertia and it foster companies to focus on their current trajectory, with the risk of becoming obsolete in the long-term (Levinthal and March, 1993).

Moving to the relationship between exploitation and exploration, a first possible distinction refers to how they can be modelled: discrete opportunities or opposites of the same continuum

(Lavie et al., 2010).

The first view consists in operationalising exploitation and exploration as two complete separate activities; however, few scholars agree with this perspective. Oppositely, assuming that the two concepts are in some way related, they can be modelized as a continuum, which is consistent with the tendency of organizations to switch over time from one aspect to the other and vice versa. According to Rothaermel and Deeds (2004), there is a natural cycle of exploitation and exploration that can be summarized as follows: the first time an organization experiments with a new technology, it is exploring; then, in the following experiment, it develops exploitative routines and becomes more familiar with that knowledge; consequently, exploration evolves into exploitation and vice versa. This theory is supported also by Holmqvist (2004), arguing that exploitation can become a cause of exploration, or exploration a cause of exploitation, due to dissatisfaction with one of the two dimensions.

These studies introduce a first possible concept of ambidexterity, called temporal, which is deeply investigated in the next section. This represents the traditional theory, supported by March (1991), in which the two concepts are conceived as incompatible and cannot be pursued at the same moment since they are too different.

Nevertheless, there is another interesting and more innovative theory, supported by Gupta et al. (2006), which points out the possibility to conceptualise exploitation and exploration as two ends of the same continuum or as orthogonal variables, simultaneously achievable. Obviously, the latter view is strictly related to the concept of ambidexterity, since the orthogonal conceptualization enables to examine the implications of the interrelationship between the two approaches (Lennerts, Schulze and Tomczak, 2019).

In sum, exploitation and exploration can be described and outlined with some keywords, introduced by March (1991): exploitation is related to “refinement, choice, production, efficiency, selection, implementation, execution.”, exploration to “search, variation, risk taking, experimentation, play, flexibility, discovery, innovation”.

2.2 Ambidexterity

2.2.1 Modes of Balancing Exploitation and Exploration

As aforementioned, March (1991) argues that both exploration and exploitation are essential for long-run adaptation, but the two are almost always fundamentally incompatible. By Gupta et al. (2006), the March's idea can be modelled as a zero-sum game where exploration and exploitation compete for scarce organizational resources. As already explained, March is one

of the first authors who considers the constructs together and points out the need to balance them; however, he does not define the expression “ambidexterity” in his article.
Only two years later, Levinthal and March (1993) develop the idea of maintaining an equilibrium between exploitation and exploration to avoid falling in the capability-rigidity paradox. Nevertheless, achieving this goal is complicated, not only considering the difficulty of determining the appropriate balance, but also because of the several ways in which the learning itself contributes to asymmetries.
O’Reilly and Tushman (2008) define ambidextrous capabilities as the set of paradoxical skills required to manage the two fundamentally different processes. Managing these two divergent processes comes from the necessity of exploiting existing resources and refining products to be competitive, and simultaneously exploring new technologies and developing new products, to not become obsolete due to changes in markets and enhancing long-term competitiveness (O’Reilly and Tushman, 2013).

According to extant literature, there is a general consensus about the merits of balancing exploration and exploitation, but a little agreement on the means to achieving such balance (Adler et al., 2009), which can be led back to four main alternatives: temporal separation, organizational separation, domain separation and contextual ambidexterity.

The first concept, temporal separation, also defined as sequential ambidexterity, refers to reaching the balance through consecutive shifts from exploitation to exploration during time, as already anticipated in the previous section. With this configuration, firms alternate longer periods of exploitation and shorter periods of exploration (Gupta et al., 2006).
According to this definition and starting from the idea that mindsets and organizational routines are radically different, organizations experiment long cycles in which technology evolves in an incremental way, interrupted by short and radical technological breakthroughs (Tushman and Anderson, 1986). In doing so, companies avoid conflicting pressures of simultaneous exploitation and exploration, gradually and slowing adjusting their tendencies to exploit or explore (Lavie and Rosenkopf, 2006). The temporal shifts from one activity to the other are not trivial and entails the necessity of developing efficient plan to handle transitions from one mode to the other (Lavie et al., 2010).
This first possible vision is supported by some scholars (e.g. Nickerson and Zenger, 2002; Siggelkov and Levinthal, 2003), and it is worthy remarking that the sequential ambidexterity can be valuable for small companies operating only in one domain, since some studies have examined the idea that, within a single domain, exploitation and exploration are generally

mutually exclusive (Gupta et al., 2006). Hence, in the literature, several researches have demonstrated the merits of exploitation and exploration temporal sequencing, suggesting primary an exploration engagement followed by a gradual refinement (Siggelkov and Levinthal, 2003).
This is a viable solution to achieve a balance, but it does not support the idea of defining this equilibrium as ambidexterity, since it does not simultaneous pursue exploitation and exploration and it does not view the two concepts as orthogonal (Gupta et al., 2006). Indeed, as observed by Hughes (2018), the most recurring concept considering all scholars' definitions of ambidexterity is simultaneity.

All the other three possible ways of balancing exploitation and exploration are based on reaching the equilibrium in a simultaneous way, as company should develop the ability to pursue at the same time incremental and discontinuous innovations, keeping contradictory process and cultures within the firm (Tushman and O'Reilly, 1996).
This idea of pursuing two different strategies is recent since, in the traditional vision of strategy, companies have to make an explicit choice, and the ones attempting to pursue different strategies result in being "stuck in the middle" or mediocre at both exploitation and exploration (Porter, 1980). If exploitation is about efficiency and variance reduction and exploration about search and embracing variation, ambidexterity is about doing them at the same time (O'Reilly and Tushman, 2008), in accordance also to He and Wong (2004), who define ambidextrous organizations as firms capable of operating simultaneously exploitation and exploration. The fundamental idea behind ambidexterity is the achievement of long-term success that requires to satisfy current demands - existing needs-, while simultaneously being prepared for tomorrow's developments - future needs (Gibson and Birkinshaw, 2004).

A possible solution is structural ambidexterity, concept perfectly analysed by Tushman and O'Reilly (1996), who define ambidextrous organizations as constituted by highly differentiated units with structural integration, so that each one exhibits internal consistency in activities and routines, whereas across units there is inconsistency.
Structural separation establishes differences across organizational departments in terms of mindsets and orientations (Golden and Ma, 2003), where the exploitative units are devoted to maximising efficiency with a large and centralized structure, whereas the explorative divisions are devoted to innovating with small and flexible structure (Lavie et al., 2010).
Sometimes separation implies even a physical separation creating dedicated offices, buildings, or separate geographical locations (Kraner and Mahagaonkar, 2018). Keeping small and

autonomous units allows employees to feel responsible for the results, encouraging exploration's culture and, at the same time, taking advantage of benefits coming from size. Moreover, with this system, organization size should not be seen as controller to slow down the process according to decision making decentralization, but as a factor to leverage economies of scale and scope in the exploitation domain. With this organizational structure, firms also create multiple mindsets with a simultaneous tight and loose culture; tight because people should be open to innovation with spontaneous and risk-taking behaviours, loose because the way in which these values are expressed change according to the type of innovation required. This double aspect is the base to have a common overall culture, a fundamental and glue factor in this kind of organization (Tushman and O'Reilly, 1996). However, this solution suits large firms but not small ones, as Voss, Sirdeshmukh and Voss (2008) find that Small and Medium Enterprises (SMEs) lacking slack resources tend to prioritize exploitation to have better returns on them.

Structural separation could be necessary when the two orientations are so different that they cannot effectively coexist; anyway, companies must be careful because separation could also lead to isolation, as many R&D units have failed to get their ideas accepted since they were too far away from core business (Gibson and Birkinshaw, 2004). Therefore, for these authors, structural separation cannot be the final solution but only a temporary one, since it has its merits but also some tricky drawbacks.

According to Jansen et al. (2009), structural separation alone provides an important but not sufficient support to become ambidextrous; hence, authors conclude that two additional mechanisms are necessary to allow companies to be efficient in balancing the two different orientations. These mechanisms are:

- *Senior team social integration:* allows to reconcile conflicting goals across spatially distributes units;
- *Cross-functional interfaces:* provide means to keep multiple innovation streams connected and thus facilitate the generation and recombination of antithetical knowledge sources, considering their ability to deepen flows of knowledge between units without interrupting their internal processes.

With this organizational structure, coordination is a necessary step in achieving ambidexterity, and the separation of the two different units is not the crucial task, since the process by which these units are integrated has a greater importance, as O'Reilly and Tushman (2008) suggest. Although each department has its orientation, the coordination effort is on behalf of the senior-management team, which faces the challenge of solving and synchronizing conflicting pressures, with the necessity to develop a proactive management style (Lavie et al., 2010). As demonstrated by the framework proposed by Ossenbrink, Hoppmann, and Hoffmann (2019), structural separation is pursued when companies perceive few and clear opportunities but there is a huge gap between the competences required and the actual ones.

The structural separation is for sure the most studied organizational structure to reach the simultaneous balance between exploit and explore, since it is the simplest one. Nevertheless, companies should be very careful in pursuing this strategy, as the drawbacks can be more than the advantages and, in order to solve the key issues, top management has a crucial role.

The third way to reach ambidexterity is represented by domain separation, meant as carrying out exploitation and exploration in different domains. The underlying concept is that organizations seeking for equilibrium do not need to reconcile exploitation and exploration within each domain, as long as an overall balance is maintained across domains (Lavie et al., 2010).

Researches on this topic are quite rare. Lavie and Rosenkopf (2006, p.798) consider exploitation and exploration's implications for interorganizational learning, recognizing that "collaboration with partners facilitates learning by accessing new knowledge residing outside a firm's boundaries and by collaboratively leveraging existing knowledge with partners". Therefore, alliances could become a remarkable vehicle for the two strategies. Moreover, the conflicting pressures coming from exploitation and exploration constrain enterprises' abilities to simultaneously pursue them within a single domain; however, companies may still be able to balance exploration and exploitation by gradually shifting from one activity to the other one within different domains, thus achieving balance across domains.

Following again Lavie and Rosenkopf (2006), the focus is shifted on potential alliances of companies, with two main possible solutions: function domain, where the dualism exploit-explore is represented by knowledge-leveraging versus knowledge-generating alliances – i.e. production and marketing against R&D collaborations; structure domain, where the dualism is defined by prior versus new partners. The use of alliances enables to mitigate the internal resources allocation constraints, but companies face trade-off also focusing on a single domain. Therefore, the best solution is achieving balance across domains by exploiting in the function one while exploring in the structure one, or vice versa, for instance by forming R&D alliances – i.e. function exploration – with prior partners – i.e. structure exploitation.

This ambidexterity configuration allows to avoid the resource allocation trade-off and internal coordination issues related to structural separation, since alliances can serve to carry out one type of activity, while the other one is pursued internally (Lavie, Kang and Rosenkopf, 2011). In this sense, Hernandez-Espallardo, Sanchez-Perez and Segovia-Lopez (2011) demonstrate that inter-organizational learning processes support the simultaneous implementation of both exploitation and exploration. Additionally, Gupta et al. (2006) point out that the two strategies are mutually exclusive within a single domain, so they could take place in complementary domains, without competing for the same and scarce resources. However, this article applies the idea to technologies and markets, without focusing explicitly on the alliances. Moreover, the proactive management by senior team is not fundamental, and the challenge shift to identifying the domains in which exploiting and the ones in which exploring (Lavie et al., 2010). Therefore, domain ambidexterity is very risky for companies, since it entirely relies on outside partners to provide the missing capability (Hughes and Perrons, 2011). Moreover, very few researches and articles exist on this form of ambidexterity and it is difficult to conceptualize its real value and efficiency (Hughes, 2018).

The last possible direction is represented by contextual ambidexterity, which consists in shifting the focus from the organizational level to the individual one.
Gibson and Birkinshaw (2004) believe that equilibrium should be achieved not by creating separated unit; on the contrary, they suggest to “build an organization context that encourages employees to make their own judgements and to best split their time between the two activities”. They do not explicitly talk about exploitation and exploration, but they define ambidexterity as the simultaneous representation of alignment – i.e. exploitation – and adaptability – exploration-, which constitute a separate, but interrelated, non-substitutable element. The first activity refers to coherence among all parts, with the aim of working together with the same objective, whereas the second one refers to the ability of quickly rearranging activities to meet changes in the environment. Therefore, in contextual ambidextrous companies, “every individual in a unit can deliver value to existing customers in his or her own functional area, but at the same time every individual is on the lookout for changes in the task environment and acts accordingly” (Gibson and Birkinshaw, 2004, p. 211).
This concept of ambidexterity differs from the other ones because it does not imply the creation of different organizational structures, as it entails the generation of a set of processes and systems that enables individuals to decide how to divide their time between the two conflicting activities (Tushman and O’Reilly, 1996). Indeed, it allows individuals to consider at the same time exploitative and explorative aspects of their work (Simsek, 2009): by principle, employees

are defined as exploitative; anyway, they are expected to become explorative when the situation demands it (Kraner and Mahagaonkar, 2018). Following Gibson and Birkinshaw (2004), this kind of ambidexterity is typical of the frontline, since workers have to decide how to act in specific and unexpected situation, and this can create conflicts.

Contextual ambidexterity shows that cultural values which promote innovation coexist with quality and efficiency, creating the challenge to manage the contradictions of exploitation and exploration within an organizational unit.

Compared to structural separation, this is potentially a more sustainable model because it facilitates the adaptation within an entire business unit, not just between separate functions in charge of different tasks, and it avoids coordination issues (Gibson and Birkinshaw, 2004). However, in this configuration, leadership becomes more essential than in the other ones, since the leader has to spur workers to select the right approach in each situation (Raisch and Birkinshaw, 2008). According to the framework developed by Ossenbrink el al. (2019), contextual ambidexterity is suitable for companies when the perceived number and uncertainty of opportunities is high, and the perceived distance of new opportunities from the organization's capabilities is low. Another crucial difference from structural ambidexterity is the role of senior management, which passes from defining the best structure to managing trade-off between functions to develop the right, single context in which individuals should act (Zaidi and Othman, 2015). Anyway, this is not enough to simply create a supportive environment, as discipline and trust are necessary too; the higher these factors are, the higher the level of ambidexterity will be (Gibson and Birkinshaw, 2004).

Recently, scholars have developed also a new concept of ambidexterity, defined by Ossenbrink el al. (2019) as hybrid, which is the combination of element coming from both structural and contextual perspectives. The authors suggest that this approach is suitable when the companies operate in difficult situations, where opportunities are perceived as numerous and uncertain, requiring different organizational culture and capabilities to pursue them.

The belief that structural and contextual ambidexterity can be combined has already been explained in the past, as Gibson and Birkinshaw (2004) argue that these two approaches differ in many aspects, but they could be viewed as complementary. In detail, the hybrid ambidexterity is not characterized by a precise definition, since it is a combination of structural and contextual approaches, using them concurrently to leverage their respective advantages; anyway, each company can differ from the others by choosing a different mix of the two elements (Ossenbrink el al., 2019).

2.2.2 Antecedents

After having described exploitation and exploration strategies and the principal ways in which they can be balanced to achieve ambidexterity, this sub-section illustrates all the possible antecedents of ambidexterity addressed by the extant literature.

Table 4 summarise the major researches with the respective antecedents analysed.

AUTHORS	ANTECEDENTS STUDIED
Gibson and Birkinshaw (2004)	• Organizational context (i.e. stretch, discipline, support and trust)
Jansen, Van den Bosch and Volberda (2005)	• Environmental (e.g. local environmental dynamism, competitiveness, etc.) • Organizational (i.e. decentralization, formalization and connectedness)
Raisch and Birkinshaw (2008)	• Structural • Leadership-based • Contextual
Lavie et al. (2010)	• Environmental (e.g. environmental dynamism, competitive intensity, exogenous shocks, etc.) • Organizational (e.g. age, size, slack resources, culture, absorptive capacity and structure, etc.) • Senior management mindset (e.g. risk aversion, past experiences, performance feedback, etc.)
Josephson, Johnson and Mariadoss (2016)	• Firm maturity • Financial slack • Strategic slack

Table 4: Notable papers and relative antecedents of ambidexterity examined

According to the topics of this work, the focus is just on the effect of two antecedents: slack resources and SMTs&ICTs. The former is interesting since it is particularly stressed by the extant literature; for instance, Cao et al. (2009) demonstrate that the simultaneous strategy exploration plus exploitation is possible and desirable for companies with resources' availability. On the other hand, SMTs are growlingly catching the attention of scholars, according to the importance of enterprises' ICTs adoption in the last decade (Walsham, 2017).

Slack resources consist in additional assets available to an organization during a planning cycle (Nohria and Gulati, 1996). In other words, they are capitals and capabilities available for redeployment. The focus is especially on financial slack, which are linked to the level of liquid assets available to an organization (Voss et al., 2008).
Scholars differ on their opinions regarding the impact of this antecedent on innovation.

A first stream argues that they can enhance search and innovation, simultaneously avoiding negative consequences in case of failure. Marín-Idárraga and Cuartas-Marín (2019), for instance, certify that organizational slack has a positive and significant effect on innovation attitude.

A second stream notes that firms with slack resources continuously support current operations rather than innovation, because they are less willing to explore rather than other enterprises which, having no excess, see exploration as the only way to survive (Lavie et al., 2010).

Voss et al. (2008), in accordance with the first stream mindset, argue that organizations with few resources are more likely to introduce innovation with minimal and incremental improvements, whereas the ones with significant resources are associated with product exploration because they can face uncertain investments and returns. Therefore, they hypothesize a negative influence of slacks over exploitation, and a positive one over exploration, without finding a support with the analyses done. Nevertheless, Josephson et al. (2016) managed to confirm the two aforementioned hypotheses, demonstrating empirically that enterprises with greater (less) financial slack are more focused on exploration (exploitation). Concerning ambidexterity, organizations with slacks are in a good position to achieve an equilibrium between exploitation and exploration, because supplementary resources could be allocated to leverage on both the two dimensions and respond efficiently to market needs (Sirmon, Hitt and Ireland, 2007). This is true also for SMEs, which require financial slack to balance exploitative and explorative innovations (Chang and Hughes, 2012). However, as pointed out by Lubatkin et al. (2006), SMEs face complex issues, because small firms lack the resources to manage a contradictory process as ambidexterity is. SMEs differ from larger enterprises since they have more stringent limitations; this imply more difficulties for them in efficiently allocating the scarce resources (Andriopoulos and Lewis, 2009). This is proved also by Ebben and Johnson (2005), who empirically show how small organizations gain more benefits from pursuing a one-side strategy, rather than simultaneously focusing on the two approaches.

In sum, “rich firms have the resources to exploit and explore simultaneously, whereas firms with less resources may not be able to afford such a complex strategy” (Raisch and Birkinshaw, 2008, p. 395).

Moving on to the second antecedent, SMTs mainly consist in physical or intangible ICTs components (Bharadwaj, 2000).

The underpinning principle is that digital technologies allow companies to achieve both exploitation and exploration, and thus ambidexterity (Sher and Lee, 2004). Xue, Ray and Sambamurth (2012) demonstrate that enterprises can invest in ICTs to improve existing operations' efficiency – i.e. exploitation – or to support the development of new products – i.e. exploration-, and the investment decision is led by the environmental dynamism.

Similarly, Lee, Lim and Sambamurthy (2008) prove that exploitation is triggered by higher levels of internally oriented ICTs resources, like commodities and shared service infrastructure, which aim at facilitating streamlined data and communication within the firm. On the contrary, exploration is enhanced by externally oriented ICTs resources, a set of specialized applications with the goal of supporting the specific task to cope with environmental dynamics.

Revilla, Prieto and Rodriguez-Prado (2007) consider the convergent and divergent dimensions of the ICTs system: the former refers to connecting people, thus facilitating coordination and communication of tacit knowledge; the latter refers to supporting retrieving and synthesizing ideas and knowledge, which can be applied to problem solving or creative action. The authors clarify how companies, when combine these two aspects of ICTs, reach higher levels of ambidexterity in the context of product development. That is confirmed also by Soto-Acosta, Popa and Martinez-Conesa (2018), who clarify that a combination of ICTs with other resources and capabilities have a positive effect on innovation ambidexterity, arguing that ICTs capability simultaneously enhance exploitation of existing knowledge and new opportunities' exploration. The positive contribution of ICTs to ambidexterity is confirmed also by Ling, Zhao and Wang (2009), which show that its positive influence over organization ambidexterity when it is mixed with business processes.

Anyway, ICTs alone are not enough to generate competitive advantage; for this reason, companies have to combine it with other critical resources in order to boost their innovativeness (Kmieciak, Michna and Meczynska, 2012).

2.2.3 Ambidexterity's Effect

Once explained the ways in which exploitation, exploration and ambidexterity could be implemented, it is crucial to review also their influence over companies.

According to Benner and Tushman, (2002), exploitation reinforce existing knowledge and skills, bringing stable gains in the short-term but creating difficulties in adapting to changes and suffering in the long run. Oppositely, exploration depart from existing knowledge, developing new solutions and causing losses in the short-term, but accumulating capabilities that can be useful in the future. Following these ideas, Luo, Kumar, Mallick and Luo (2018) consider the impact through time and assume an inverted U-shape relationship between exploitation and firm performance, and their analysis shows a positive but non-significant effect in the long run. Authors suspect that these results are determined by their dataset, which is formed by high technology Chinese companies that, according to their young age, authors suppose they have not turned into the final part of the curve yet. Additionally, they hypothesize and confirm a "horizontal S" relationship between exploration level and firm's performance, so that, once enterprises acquire adequate knowledge, their performance improves. In support of this argument, Auh and Menguc (2005) prove that exploration positively influence market-share growth and sales growth, two measures of long-term performance rather than short-term ones. Several works agree on exploitation and exploration positive consequences over performance, but the magnitude of such benefits vary across companies and it is determined by organizational and environmental contingencies (Lavie et al., 2010).

Moving to ambidexterity, it is not always analysed considering one of the four perspectives – i.e. temporal, organizational, domain separations and contextual ambidexterity; indeed, authors usually conceive ambidexterity only as generic equilibrium between exploitation and exploration (Lavie et al., 2010).

The basic idea beyond ambidexterity, made explicit by Tushman and O'Reilly (1996), is that a balance of exploitation and exploration can lead to superior organizational performance. This because firms which achieve ambidexterity should be well-placed to overcome the success trap related to excessive exploitation and failure trap related to excessive exploration (Hughes, 2018). In this work, organizational performance are analysed in terms of BP and IP, even if some authors, like Sarkees and Hulland (2009), have analysed also other dimensions, demonstrating that an ambidextrous enterprise has a positive effect not only on revenues, profits and new product introductions, but also on customer satisfaction. Anyway, not all studies have pointed out positive results regarding the equilibrium and the interaction between exploitation and exploration.

Starting by analysing the monetary performance, Ebben and Johnson (2005) point out negative relationships because, by studying the strategies of small companies, they demonstrate that firms attempting to pursue both efficiency – i.e. exploitation – and flexibility – i.e. exploration – perform less well than those with a single, focused strategy. The authors are not focused on the ambidexterity concepts, as they simply certify the impossibly to pursue two strategy at the same time, thus involuntarily suggesting that the only possibility to balance exploitation and exploration is the temporal separation. This idea is supported also by Venkatraman, Lee, and Iyer (2007), as they prove how sequential ambidexterity has a positive effect on firm sales growth; however, they do not confirm the hypothesis that simultaneous ambidexterity has a positive influence on firm sales growth. Nevertheless, it is clear that two strategies are not incompatible, because the significant cash flows coming from exploitation-related activities provide financial assets necessary for exploration, whereas exploration activities provide capabilities and technological assets to support the renewal of exploitation activities (Garcia, Calantone and Levine, 2003).

One of the most valuable contribution comes from He and Wong (2004) who, focusing on technological innovation – meant as how enterprises commercialize new technological knowledge and ideas into new products –, demonstrate the following hypotheses:

- A positive effect of the interaction between exploitation and exploration strategies over firm performance, and a negative one related to their imbalance;
- Ambidextrous organizations – meant as scoring high on both exploiting and exploring – exhibit smaller performance's variation, relative to their mean values of sales growth rate, than enterprises which are specialized in explorative innovation strategy.

If the second hypothesis is quite intuitive, since it is natural expecting high variation in company that are strongly focused on exploration, the first validates the theory that ambidexterity can lead to higher performance, idea already proposed in literature but, until this publication, with no empirical evidence.

Also Lubatkin et al. (2006) prove a positive association between firm's ambidexterity and subsequent relative performance. This study is about SMEs, assuming as enterprise's performance the profitability and growth compared to competitors.

Nevertheless, there are also some cases in which authors perfectly and directly express how they conceive ambidexterity, for instance by considering the domain separation.

The first case comes from Lavie et al. (2011), who support the vision of domain separation and demonstrate how traditional forms of balance within a domain is disadvantageous, because firms that look for it do not benefit neither in short nor in the long-term, and they could expect a decline in market value and in net profit; on the contrary, firm's performance is positively related to balance between exploration and exploitation across function and structure domains. A very interesting aspect of this study is that organization's performance are measured both in the short-term – with the net profit -, and in the long-term – with the enterprise market value.

Gibson and Birkinshaw (2004), in accordance to their vision of contextual ambidexterity, prove that higher level of ambidexterity in a business unit implies higher level of performance. However, the performances are assessed in a subjective way, since they collected the data through interviews with senior and middle management regarding the performance over the last five years.

Considering all these contributions, it can be concluded that ambidextrous firm have the possibility to reach higher monetary performance, even if there is no clear evidence on which ambidexterity alternative would allow to achieve the optimum results and which organizational structure should be adopted.

Passing to the studies on firms' IP, it is first of all necessary to remark two possible research streams, illustrated in Figure 3: the first one recognizes a direct and linear relationship between exploitation and exploration and distinguishes two IP – i.e. incremental and radical; the second one analyses the effects over the overall IP, without differentiating between incremental and radical innovation, testing also a curvilinear relationship.

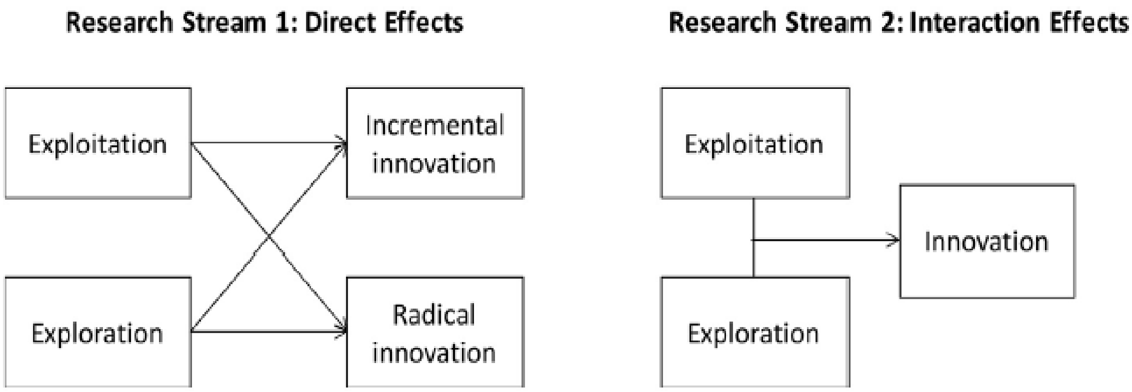

Figure 3: Research streams of exploitation and exploration's effects on IP (Lennerts et al., 2019)

Starting from the first stream, Atuahene-Gima (2005) analyses IP in terms of new product development, differentiating between incremental and radical innovation depending on the amount of technological changes and the targeted customer.

The author empirically determines what can be reasonable to expect: positive relationships exploitation-incremental IP and exploration-radical IP; negative relationships exploitation-radical IP and exploration-incremental IP. Nevertheless, he hypothesizes also an interaction effect of exploitation and exploration on incremental and radical IP.

The findings show that there is no supporting evidence when analysing incremental IP, but there is a surprisingly negative influence of interaction on radical IP. This result is counterintuitive and suggests that exploration could be more valuable when matched with a low level of exploitation, an outcome opposed to the ambidexterity concept.

Similar finding comes also from other authors, such as Arnold, Fang and Palmatier (2011), who analyse firms' orientation in terms of customer acquisition or customer retention. As a result, increasing customer retentions seems to improve incremental IP, whereas acquiring new customer should lead to resource exploration, which is positively related to radical IP. They also demonstrate that simultaneously high orientation to both acquisition and retention improves innovation.

Additionally, Hernandez-Espallardo, Molina-Castillo and Rodriguez-Orejuela (2012), analysing both intra-organizational and inter-organizational aspects, conclude that intra-organizational exploitation is positive related to incremental innovation, whereas radical innovation is positive influenced by inter-organizational exploration, which is the most complicated but necessary learning mechanism. Their findings confirm that companies should previously support radical innovations with inter-organizational exportation and, once the knowledge is internalized, they should exploit these capabilities with intra-organizational learning.

Concerning the second stream, Atuahene-Gima and Murray (2007) analyse the overall effect of exploitation and exploration on new product development, hypothesizing an inverted U-shape relationship for both the two dimensions. Actually, a high level of exploitation can cause difficulties in development and adoption of new directions, whereas a high level of exploration can reduce the investments' reliability and a great amount of new ideas could be too complicated to be managed. Nevertheless, the hypothesis testing indicates that in both cases the relationship must be modelled by a U-shape, suggesting that, as organizations exploit and explore more, they achieve high efficiency in the learning processes, which translate into better IP. Wang and Lam (2019) underline this concept, pointing out that, as long as an organization learns, it will positively influence its IP.

Equal hypothesis but divergent results come from Li, Chu and Lin (2010) who, examining new product development performance, demonstrate that exploitation and exploration have an inverted U-shape relationship with them, as previously hypothesized by Atuahene-Gima and Murray (2007), stressing how exploitative and exploratory learning activities become detrimental beyond a certain level.

Proves of positive influence of exploitation and exploration on IP come also from He and Wong (2004), who use the product innovation intensity as mediator of the relationship exploitation-Business Performance (BP) and exploration-BP, demonstrating the positive impact of both the two strategies.

Atuahene-Gima and Murray (2007) certify also that the interaction effect between exploitation and exploration is negatively related to new product development. Therefore, the authors suggest that, at low levels of exploitation, increasing the level of exploration leads to higher IP; on the contrary, at higher level of exploitation, strengthening exploration has the opposite result – i.e. worsening the performance.

The study by Li et al. (2010) supports also the existence of a negative interaction between exploitation, exploration and new product development performance, concluding that the appropriate strategy should be focusing only on exploiting or on exploring.

Anyway, not all the studies have found negative relationships between ambidexterity and IP. In this sense, the article by Lee, Woo and Joshi (2017) is very interesting, as they depicted and demonstrated an ambiguous scenario: firms with a high level of exploration, by increasing their exploitation, can enjoy higher new product development performance; on the contrary, companies which strengthen the exploration effort when exploitation is low, achieve worse performance.

This perfectly shows how it is difficult to perfectly determine the consequences of combining exploitation and exploration strategies – i.e. ambidexterity approach – on IP.

More clear result comes from Katila and Ahuja (2002), as they discover that the interaction of exploitation and exploration is positively related to the number of new products introduced by a firm, stating that companies able to achieve a balance between the two approaches would benefits from it. This study provides also another important contribution because, even if the hypothesis of an inverted U-shape relationship between exploration and IP is not supported, in favour of a positive effect, the outcomes of the investigation confirm the existence of this relationship – i.e. inverted U-shape – between exploitation and IP, supporting the already mentioned concepts.

Another evidence of the positive interaction comes from Nerkar (2003), who determine how a combination of exploitation and exploration positively affects the creation of new knowledge.

Lennerts et al. (2019) integrate the two aforementioned streams, examining the interaction effects of exploitation and exploration on both incremental and radical IP, and testing also non curvilinear correlations, thus expanding the study by Atuahene-Gima (2005). They verify the hypothesis that exploration has an inverted U-shape role on exploitation's repercussion over incremental IP.

This study proves how an interrelationship of exploitation and exploration is more beneficial than the contributes of exploitation and exploration separately, thus supporting the argument that, if new knowledge is not explored, incremental innovation is hard to sustain. Nevertheless, they do not find support for the exploitation curvilinear effect on exploration-radical IP relationship, showing how companies can have difficulties in transform distant knowledge into radical products, even if this is complemented with exploitation of current knowledge.

After having investigated the impact of ambidexterity on IP, it can be inferred that the assumption of positive consequences coming from high exploitation and high exploration is not always supported; indeed some authors prove that, sometimes, high-high combination can bring negative result, suggesting a high-low balance.

2.2.4 How to Model Ambidexterity

Once outlined the context of ambidexterity, it is important to give an overview regarding how ambidexterity is measured in literature. Indeed, even if there is a broad consensus that ambidextrous organizations engage in both components, it is unclear whether these firms' effort is focused on the combined magnitude of both exploitation and exploration, or on matching the magnitude of these two types of activities.

He and Wong (2004) point out that these two separate interpretations of ambidexterity exist in literature. Cao et al. (2009) deepened this theory, developing the concepts of combined and balance dimensions, which determine how to operationalize the construct. The former affirms that each strategy could help in leveraging the effect of the other, and resources can be simultaneously deployed in both approaches; hence, ambidexterity should be computed as the product or sum of exploitation and exploration, which evaluate their absolute magnitude values. The latter states that exploitation and exploration should be in equilibrium, in order to mitigate the risk associated to becoming obsolescent or managing too much novelty and knowledge; hence ambidexterity should be modelled with the absolute difference between exploit and explore. Therefore, different results in the ambidexterity level of a company can be found, according to the perspective adopted.

Both these two visions are present in literature: the multiplication is used by Gibson and Birkinshaw (2004), Morgan and Berthon (2008), Jansen et al. (2005), whereas the absolute difference is used by Chang and Hughes (2012). In some cases, authors opted for considering at the same time the two alternatives, adopting both multiplication and absolute difference (e.g. He and Wong, 2004; Cao et al., 2009). Going into detail, the combined dimension suppose that exploitation and exploration can be supportive one to the other, concept which is at the base of the domain and structural separation vision of ambidexterity. On the other hand, the balance dimension is related to the traditional definitions of ambidexterity, which conceives exploitation and exploration as two opposite activities to be balanced.

A remarkable contribution is offered by Cao et al. (2009), who demonstrate that combined and high level of both combined and balance dimensions are positively related to firm performance, whereas the positive relationship between balance dimension and enterprise performance is not supported. These results confirm that balancing exploitation and exploration is not sufficient to be ambidextrous, because low performance in both dimensions means that the company do not perform well, and not that it is ambidextrous. This is argued also by He and Wong (2004), showing that very low levels of both exploitation and exploration does not contribute to superior firm performance; indeed, even if reaching an equilibrium is a necessary step, since the absolute difference between exploitation and exploration is negatively related to enterprise performance, it is not enough to label a firm as ambidextrous. In this sense, Simsek (2009, p.603) states that "an organization with low levels of exploitation and exploration is 'balanced', but not ambidextrous".

Lubatkin et al. (2006) try to provide a method, empirically supported, to assess ambidexterity in SEM, since there was no widely accepted measure of it.
They experiment the three possible modes: sum, multiplication and absolute value of the subtraction. By leveraging on regressions, they prove that the sum is the best method, as the other two alternatives provide higher loss of significance. This research is limited to the context of SMEs operating in the American market; anyway, the findings are supported also by other recent papers (e.g. Tuan, 2016; Mardi et al., 2018) which take into consideration a different sample. Therefore, ambidexterity should be computed as sum, since the additive model contains the least information loss in aggregating exploitation and exploration into the latent factor ambidexterity (Tuan, 2016). However, in several cases (e.g. Gibson and Birkinshaw, 2004; He and Wong, 2004), scholars opt for the multiplication, since it represents the most classical way to predict the interaction between two variables. In this sense, it is relevant also the analysis proposed by Menguc and Auh (2008) and Suzuki (2019), who decided to mean-centre exploit and explore's constructs in order to detect multicollinearity, a typical issue arising when dealing with interaction effects.

In conclusion, ambidexterity can be modelled in three different ways: sum, multiplication and absolute value of the subtraction. Anyway, there is no full consensus between scholars regarding which method should be used, because each one has its own strengths and weaknesses:

- *Sum*. It provides the lowest loss of significance so it should be the best solution, as proved by Lubatkin et al. (2006). Nevertheless, it completely neglects the perspective of balance dimension; indeed, by following this operationalization, a firm extremely oriented in pursuing just one strategy will be as ambidextrous as one which has medium score in both the two dimensions. For instance, a company scoring 5 and 1 respectively in exploitation and exploration will have the same ambidexterity score of an enterprise with 3 in both dimensions;
- *Multiplication*. The most adopted, it captures the interaction effect, solving the issues associated with the sum. The main drawback is represented by multicollinearity, which could affect the analysis. Additionally, this method overemphasizes the increment in one dimension: in practice, by implementing this operationalization, a company scoring 2 in both dimensions appears less ambidextrous than one scoring 2 and 3, which in turn appears less ambidextrous of one scoring 2 and 4, and so on. This fact is coherent with the combined dimension concept, but not with the ambidexterity goal of simultaneous pursuing exploitation and exploration (Tushman and O'Reilly, 1996);
- *Absolute value of the subtraction*. This alternative is perfectly in line with the balance dimension principle and, for this reason, it perfectly describes the simultaneous pursuit of both dimensions. However, by nature, this operationalization completely neglects the orientations' magnitude, since a firm with very low score in both exploit and explore could seem ambidextrous even if it is neither exploitative nor explorative. For instance, by following this method, a company scoring 1 in both dimensions appears equal ambidextrous of one scoring 5 in both dimensions.

2.3 Industry 4.0 and Smart Manufacturing Technologies

Firms operating in the manufacturing field are today exposed to several challenges and difficulties. Indeed, as highlighted by Brousell, Moad, and Tate (2014), the context is requiring increasingly high levels of agility, versatility and responsiveness to changes in customers' behaviour.

In order to survive in this complex environment and to address the aforementioned challenges, firms need to improve their flexibility in manufacturing processes.

From this perspective, it emerges the need for an effective integration between ICT and Operational Technology (OT), in order to align the two domains, thus allowing intelligent and autonomous operations (Cheng, Farooq, and Johansen, 2015). In this sense, Rashid and Tjahjono (2016) affirm that, thanks to a high level of automation and digitalization, it is possible to connect and integrate in a seamless way the productions systems and the enterprise systems. This represent the starting point of I4.0, since “the goals of Industry 4.0 are to achieve a higher level of operational efficiency and productivity, as well as a higher level of automatization” (Lu, 2017, p. 1).

The first I4.0 conceptualisation was developed in 2011 in Germany as “Industrie 4.0” by a group of representatives from different fields, according to a government initiative (High Technology Strategy for Germany, 2020) with the aim of leading the technological innovation and the purpose of establishing smart factories, involving all the relevant sectors of the manufacturing industry.
Although the term was coined in Germany, most of other nations are trying to exploit the latest breakthrough innovations in order to foster the national development (Oztemel and Gursev, 2018).
In particular, an important effort has been implemented by U.S.A., where the I4.0 concept is called smart manufacturing. Indeed, the manufacturing research and development programs in the U.S.A. “focus on key technology assignments, including internet of things, big data, data analytics, cyber physical systems, system integration, sustainable manufacturing, and additive manufacturing to respond aggressively to the innovative manufacturing environment change called the fourth industrial revolution.” (Kang, Lee, Choi, Kim, Park, Son, Kim and Noh, 2016, p. 113).
Kagermann, Wahlster and Helbig (2013), supported also by Lasi, Fettke, Kemper, Feld and Hoffmann (2014), sustains that I4.0 refers to an increasingly automatized manufacturing industry, through the integration of smart technologies such as Internet of Things (IoT) and cloud computing, which permits the interconnection between digital and physical worlds, thus giving the possibility to increase the manufacturing flexibility and the amount of available data.
Additionally, Shafiq, Sanin, Szczerbicki and Toro (2016) depict and summarize the underpinning principles of I4.0, which are: interoperability, modularity, virtualization, decentralization, real-time capability and service orientation.
Oztemel and Gursev (2018) give a remarkable support in the definition of I4.0 and in describing its main principles since, after having reviewed 620 publications on this topic, they conclude that I4.0 can be described as an integrated, adapted, optimized and interoperable manufacturing process which is connected due to the utilization of sensors and systems producing, collecting, managing and analysing a huge amount of real time data.

2.3.1 The Goals of Industry 4.0

The goals of I4.0 are to "provide IT-enabled mass customization of manufactured products; to make automatic and flexible adaptation of the production chain; to track parts and products; to facilitate communication among parts, products, and machines; to apply human-machine interaction paradigms; to achieve IoT-enabled production optimization in smart factories; and to provide new types of services and business models of interaction in the value chain" (Lu, 2017, p. 3).

Several papers focus the attention on the notion of smart factories, considered as one of the main objectives of I4.0. Dalenogare, Benitez, Ayala and Frank (2018, p. 384) affirm that the new systems of I4.0 "aim to monitor and control the equipment, conveyors and products through a cycle of feedbacks that collects a great quantity of data and updates the virtual models with the information of the physical processes, resulting in a smart factory".

This concept is stressed also by Oztemel and Gursev (2018), arguing that I4.0 wants to generate "dark factories", so called because they would rely on robotic systems, which do not require light to work. Hence, plants will be managed with little or no human intervention, from the entrance of the raw material to the exit of the product: human should be involved only into a little part of the process, usually related to problem-solving (Lee, 2008). Additionally, the authors underline that also products must become smart and connected, in order to make them easily identifiable at any time and state of their own history. As a consequence, the entire supply chain would benefit and firms will be more easily connected and will more likely communicate to share data.

Sanders, Elangeswaran and Wulfsberg (2016) underline once more the relevance of smart factories and their crucial role in I4.0, arguing that intelligent factories and smart manufacturing are its major goals.

Roblek, Meško and Krapež (2016) state that I4.0 has the possibility to generate more flexible, dynamic and intelligent plants by equipping manufacturing processes and products with sensors and by adopting autonomous systems. Indeed, "the most important technology at the device or hardware level in realizing IoT, cloud manufacturing and cyber physical systems, and smart manufacturing is the sensor technology because the sensor is the most basic technology for collecting and controlling data in real time" (Kang et al., 2016, p. 120).

Another interesting point of view is also offered by Qu, Ming, Liu, Zhang and Hou (2019), as they propose a different classification of the purposes of I4.0, consisting in three main concepts:

- *Autonomous lean operation*: integrating management and new emerging technologies in order to generate autonomous automized plants, which can promptly react to unexpected changes in demand; this concept is directly related to smart factories implementation;
- *Sustainable value added*: focusing on sustainability and value added in smart manufacturing systems lifecycle, by simultaneously considering economic, environmental and social evaluation of products design, manufacturing processes and the entire supply chain;
- *Win-win partnership*: maintaining a completely open and transparent relationship with the other actors of the chain, thanks to the continuous exchange of real time information, in order to cooperate effectively.

In sum, there are several objectives which I4.0 aims to satisfy; anyway, the unifying theme is represented by the breakthrough and straightforward concept of connecting manufacturing to the digital world, as suggested by Xu and Duan (2019).

2.3.2 Smart Manufacturing Technologies

In order to make it possible to achieve the aforementioned goals, each company must embrace I4.0 by adopting and implementing the so-called SMTs. This set of breakthrough systems is crucial to enable the perfect marriage between physical and digital worlds from the viewpoint of manufacturing, concept already illustrated in the previous sub-section. The extant literature provides different and several classifications of SMTs; anyway, there is a general consensus regarding which are the leading actors of I4.0. In detail, a remarkable number papers states that IoT, Big Data and Industrial Analytics (BD&IA) and cloud manufacturing represent the core of I4.0 (Lu, 2017; Roblek et al., 2016; Schmidt, Möhring, Härting, Reichstein, Neumaier and Jozinović, 2015; Gruber, 2013; Vijaykumar, Saravanakumar and Balamurugan, 2015; Wan, Tang, Shu, Li, Wang, Imran and Vasilakos, 2016). For the sake of completeness, this work shows and describes also other technologies which have a great influence nowadays – i.e. additive manufacturing and Enterprise Resource Planning (ERP).

Internet of Things

The term IoT covers a wide number of aspects, as underlined by Miorandi, Sicari, De Pellegrini and Chlamtac (2012), who define IoT not only as the set of supporting technologies – e.g. Radio Frequency Identification (RFId), sensors, machine-to-machine communication, etc. – which can enable the vision of I4.0, but also as the collection of systems and services that can create smart objects and open new business and market opportunities.

In detail, the authors examine IoT considering four different levels of analysis: from the single

component perspective, IoT is completely relying on smart objects or things, which must possess the capability to sense physical phenomena; from the system perspective, IoT consists in a network of different systems, composed by a large number of smart objects, which deals with a huge flow of data; from the service perspective, IoT aims at finding a way to translate the data collected by the smart objects into services valuable for the final customers; from the user perspective, IoT allows to generate a set of services perfectly tailored on the specific need of the user, leading to a high level of satisfaction.
To conclude, the article presents a detailed list of the features that must be supported by IoT:

- *Devices heterogeneity*: very different capabilities are required, from the point of view of computation and communication;
- *Scalability*: it is necessary to deal with a remarkable number of entities and systems;
- *Ubiquitous data exchange through proximity wireless technologies*: smart objects need to be enabled through wireless technologies;
- *Energy-optimized solutions*: energy usually represents a scarce resource that must be managed properly and carefully;
- *Localization and tracking capabilities*: smart objects are now traceable, with several benefits in the logistics field;
- *Self-organization capabilities*: utilization of automatized systems to minimize human intervention;
- *Semantic interoperability and data management*: utilization of basic standards for language and format in order to manage the available data and thus support automated reasoning;
- *Embedded security and privacy-preserving mechanisms*: security is a basic need of IoT which should be already included and guaranteed in the design of architecture of the systems.

The great importance of IoT is underlined also by Kang et al. (2016), which stress again the key role of this technology in collecting and exchanging data acquired by smart sensors or smart objects and in enabling BD&IA, with a great impact also on the relationship with final customers and partners of the value chain (Ahuett-Garza and Kurfess, 2018; Fatorachian and Kazemi, 2018).

In sum, the extant literature exhibits a great consensus on considering IoT a crucial actor in the process of merging ICT and OT worlds, thus generating smart factories and improving the decision-making processes.

Big Data and Industrial Analytics

The previous paragraph shows how IoT sensors provide and collect an enormous amount of data from the manufacturing chain, for instance related to inventories, raw materials, etc. Therefore, it is necessary to find a way to deal with them and to analyse them. Business analytics perfectly fit with this purpose, as it consists in exploiting data coming from different sources through statistical analyses, predictive models and machine learning algorithms, in order to support and drive the decision-making process of the stakeholders (Davenport and Harris, 2007; Soltanpoor and Sellis, 2016).

First of all, it is important to remark the three most-widely recognized characteristics of big data, called "3 Vs": volume, velocity and variety (De Mauro, Greco and Grimaldi, 2016). As described by Xu and Duan (2019), volume refers to how much information is generated, affecting the reliability of the estimations, velocity refers to how fast they are produced, and variety refers to the different typologies of information which are created.

The authors underline also the necessity of some techniques to handle and analyse such an enormous amount of data. This need opens the door to industrial analytics. As determined by Dai, Wang, Xu, Wan and Imran (2019), the process of industrial analytics is made up by three stages:

a. *Data acquisition*: collection of information thanks to the already described devices of IoT – e.g. RFId tags; the main challenges of this phase are represented by finding a way to represent data and an efficient method to transmit them;
b. *Data processing and storage*: data must be cleaned, integrated and compressed with a processing phase before being stored, thus overcoming issues related to redundancy and reliability of the stored information;
c. *Data analytics*: examination of the stored data in order to extract something useful to generate business value, facing possible issues concerning security and privacy.

The last phase is particularly relevant, and can be divided into four subsequent steps of analysis:

1. *Descriptive analytics*: the historical data are explored with the aim of answering the question "what has happened?";
2. *Diagnostic analytics*: data are examined more in dept to identify the causes of an issue and to answer to the question "why did it happen?";
3. *Predictive analytics*: historical data are here examined to anticipate future trends, with the purpose of understanding "why will it happen?";

4. *Prescriptive analytics*: some algorithms are used in order to extend the previous phase and thus take decisions according to prediction of future trends, answering the question “what should I do?”.

Steps 1 and 2 are supported by a reactive approach, whereas phases 3 and 4 are characterized by a proactive approach, which represents the main purpose of companies dealing with I4.0, as it can generate value for the business.

Cloud Manufacturing

Cloud manufacturing is an innovative evolution of cloud computing defined as “a resource sharing paradigm that provides on-demand access to a pool of manufacturing resources and capabilities aimed at utilizing geographically dispersed manufacturing resources in a service-oriented manner. These services are deployed via the Industrial IoT and its underlying ICTs infrastructure, architecture models, as well as data and information exchange protocols and standards.” (Mourad, Nassehi, Schaefer and Newman, 2020). In other words, cloud manufacturing represents the latest evolution of cloud solutions, which consists in generating a shared pool of manufacturing resources available on service; this makes it possible to achieve a great level of flexibility and agility, thus satisfying and accomplishing the continuously changing requests coming from the final customers (Kang et al., 2016).
As underlined by Wu, Greer, Rosen and Schaefer (2013), adopting a distributed manufacturing configuration leads to an improvement both in short and long-term: concerning the short run, cloud manufacturing allows to reduce costs and increase efficiency; considering the long run, the relationship with the other actors of the chain will be improved. The former concept is confirmed also by Wu, Rosen and Schaefer, (2014), which affirm once again that cloud manufacturing permits to save money and enhance efficiency inside the value chain.

Another very interesting analysis is offered by Kusiak (2017), which states that two main architectures of manufacturing systems are emerging: integrated and open (or decoupled). Focusing on the latter, the author argues that the openness of manufacturing configuration entails a decoupling of design, logistics and service layers from the physical assets. For instance, some key services such as maintenance can be separated from the manufacturing enterprise. As a consequence of this radical change, the competition shifts its focus from the purchase of internal technologies to the acquisition, management and development of knowledge to configure, reconfigure and optimize the distributed services and their assets.

In sum, cloud manufacturing is changing the way companies manage and configure their manufacturing assets and systems, and it is paving the way for a future adoption of x-as-a-service solutions – i.e. design-as-a-service, maintenance-as-as-service, logistics-as-a-service, distribution-as-as-service, supply-as-a-service (Kusiak, 2019).

Additive Manufacturing

According to Kang et al. (2016), additive manufacturing is an innovative technology which aims at translating a 3D model, such as a computer-aided design file, into a physical object, by joining and cutting some materials through light, ultrasonic vibration, laser or electron beam. There can be different types of additive manufacturing, according to the kind of material or method used. In particular, if the bonding process is realized via cutting-edge method, the technology is called 3D printing. Beyond that, the paper affirms that the possible advantages of this technology over the existing manufacturing methods are represented by efficiencies in materials and resources utilization and improvement in production flexibility; on the contrary, the weaknesses consist in size limitations, imperfections and costs.

Regarding the possible benefits, Holt, Edwards, Keyte, Moghaddam and Townsend (2019) underline how additive manufacturing helps in overcoming design limitations and strongly affects the possibility to satisfy customer demand, since 3D printing entails an acceleration of the manufacturing process and enables to produce at low volume and extremely high variety (Ahuett-Garza and Kurfess, 2018).

Therefore, as confirmed by Thompson, Moroni, Vaneker, Fadel, Campbell, Gibson and Martina (2016), additive manufacturing has the potential to enhance and support several activities, including manufacturing, energy, transportation, art, architecture and military, and there is no doubt that 3D concrete printing will continue to grow and will likely becomes one of the key manufacturing technologies of the 21st century.

Enterprise Resource Planning

ERP systems are a set of managerial software which aim at integrating the different domains of a firm, by connecting most of the core business processes such as human resources, finance, production, etc. In practice, data are uploaded into the software and then translated into information to be processed in different departments. Therefore, the impact and the relevance of ERP on organization business success is clear (Mohammed, Talib and Al-Baltah, 2020). Oztemel and Gursev (2018) claim that I4.0 needs connectivity and collaboration in order to be correctly implemented, and ERP is fundamental to achieve such objectives. In detail, they summarize the benefits of ERP, especially focusing on the possibility to analyse real time data, communicate with the other actors of the chain in a transparent way and keep the final customer updated on orders' status.

2.3.3 Effects of the Implementation of Smart Manufacturing Technologies

A successful implementation of the SMTs and thus the generation of smart factories entail great benefits. In this sense, Dalenogare et al. (2018) examines the possible advantages of SMTs considering two different perspectives:

- From the market point of view, they make it possible for the companies to deliver new digital solutions to the customers – e.g. smart connected products (Coreynen, Matthyssens and Van Bockhaven, 2017);
- From the operational perspective, they lead to the optimization of the time-cost trade-off, by reducing set-up time and simultaneously diminishing the labour and material spending, thus achieving a higher productivity of the production processes (Brettel, Friederichsen, Keller, and Rosenberg, 2014; Jeschke, Brecher, Meisen, Özdemir and Eschert, 2017).

The second perspective is especially underlined and examined in the extant literature, as several articles stress the advantages of reduced resource utilization and increased energy savings (e.g. Ali and Azad, 2013; Jeschke et al., 2017), and the possibility of customizing products by producing in small batches, thus achieving more flexibility and lead time reductions (Shafiq, Sanin, Szczerbicki and Toro, 2015). Moreover, since I4.0 enables companies to collect, manage and analyse real time data, also strategic and operational decision-making processes can be improved (Kagermann et al., 2013; Porter and Heppelmann, 2014; Schwab, 2017).

Another stream of researches, consisting in a remarkable number of articles (e.g. Weyer, Schmitt, Ohmer and Gorecky, 2015; Kagermann et al., 2013; Wang, Törngren and Onori, 2015; Tortorella, Vergara, Garza-Reyes, and Sawhney, 2020; Dalenogare et al., 2018), affirms that the implementation of I4.0 reinforces digital integration along the whole value chain, thus enhancing collaboration and communication from three main perspectives: vertical integration, horizontal integration and end-to-end engineering.

- Vertical integration is related to a single firm, as it refers to the interconnection between ICTs systems belonging to different hierarchical levels of the organizational structure, up to the ERP level, in order to enable a flexible and reconfigurable manufacturing system;

- Horizontal integration oppositely refers to the possibility of exchanging real time information with the other actors of the chain, thus improving the relationships with them;
- End-to-end engineering is more related to the product domain, as it consists in the integration of engineering in the whole value chain of the product, from its design until the after-sale phase (Kagermann et al., 2013; Brettel et al., 2014; Gilchrist, 2016); hence, thanks to useful and powerful software, products can be perfectly customized.

Since the product lifecycle comprises several stages that should be performed by different corporations, the horizontal integration of corporations and the vertical integration of factory inside are considered the underpinning principles for the end-to-end integration of engineering processes (Wang, Wan, Li and Zhang, 2016).
Brettel et al. (2014) shed lights also on the opportunities and benefits related to business growth. In practice, the possibility of achieving and enhancing horizontal integration allows not only to exchange real time data, but also to share the risk along the chain and quickly adapt to changes in the market. Therefore, new business models and new ways to capture value from the final customers may emerge (Wang et al., 2016; Kagermann et al., 2013; Chryssolouris, Mavrikios, Papakostas, Mourtzis, Michalos and Georgoulias, 2009).
Moreover, the utilization of smart connected products paves the way for the connection with the final customers too, letting them play a relevant role inside the production process; obviously, this increases the chances of delivering a high-value good (Kiel, Arnold, Collisi and Voigt, 2016; Porter and Heppelmann, 2014).

Another very interesting investigation is developed by Fatorachian and Kazemi (2018), as the authors list all the possible benefits of I4.0 they deem relevant. In detail:

- *Meeting individual customer demands*: thanks to the increased involvement of clients inside the value chain, it is possible to customize the products according to their precise requests;
- *Flexible and agile engineering and manufacturing*: due to a dynamic, flexible and versatile configuration of various business elements, an agile manufacturing process is implemented, with the aim of promptly and effectively meeting the changing customer demands;
- *Improved information sharing and decision-making*: the enhancement of the data sharing process perfectly fits with the need of taking the right decisions at a very short notice, in a continuously changing and challenging environment;

- *Improved integration and collaboration*: the high level of interconnection between the different factories allows managers to monitor the performance from any location in an efficient way, thus enabling transparency and a proactive approach toward problem solving;
- *Improved resource productivity*: the implementation of SMTs diminishes the amount of resources needed to manufacture a given product – e.g. by reducing the energy consumption -, thus enhancing the productivity of the firm;
- *Mass customization*: I4.0 opens the way to the idea of producing highly customized products at low volume, while maintaining the quality of goods – e.g. by implementing 3D printing.

The analysis concludes by underlining how all these benefits can lead to an increase in competitiveness, thus to more tangible results – i.e. monetary gains.

Only few articles, within the previously highlighted ones, examine the benefits of adopting SMTs with an empirical approach – i.e. considering a real context.
In this sense, Tortorella et al. (2020) analyse the possible impact of I4.0 basic technologies over the operational performance. The study is carried out with a cross-industry analysis in the Brazilian market by issuing, in 2018, a survey to 351 firms; in detail, the questionnaire assesses the adoption level of three SMTs – i.e. IoT, cloud computing, BD&IA – and evaluates the observed variation, in the previous three years, of a given set of performance – i.e. safety, delivery service level, quality, productivity and inventory level. As a result, the authors certify that these four technologies positively affect the above-mentioned operational performance. This conclusion is confirmed also by Dalenogare et al. (2018) which, with a sample of 2225 companies, always operating in the Brazilian market, illustrate how the adoption of a wide list of technologies of I4.0 – e.g. computer-aided design integrated with computer-aided manufacturing, BD&IA, additive manufacturing, cloud manufacturing, etc. – strengthens the industrial performance of a company – e.g. product customization, product quality, energy efficiency, reduction of operational costs, workers' safety, creation of new business models, sustainability improvements, process control, etc. Moreover, the authors hypothesize and demonstrate that this relationship is affected by the economic context which firms are operating in. In particular, they prove that the positive effect of SMTs over industrial performance is lower in emerging countries rather than in developed ones.
This concept is underlined also by Kagermann (2015), arguing that emerging countries can even perceive differently the technological changes, as the diffusion of SMTs may be based on different needs compared to developed countries. Therefore, as a consequence, also the perceived value of technologies can differ, thus affecting their attractivity (Castellacci and

Natera, 2013).

In this sense, McKinsey (2015), through a survey, clearly determines that, in implementing SMTs, the variable country should not be neglected. Indeed, the answers of managers working in the U.S.A. are different from the ones operating in Germany and China.

Another significant contribution is brought by Sommer (2015, p. 1512), which considers the role of business size in the adoption of breakthrough innovation. In practice, he examines the difficulties of SMEs in tackling the challenges of I4.0, leading to the conclusion that "The smaller SMEs are, the higher the risk that they will become victims instead of beneficiaries of this revolution". In detail, considering the Germany industry, he hypothesizes a negative influence of business size over the willingness to actively deal with the subject I4.0. As a final recommendation, the author suggests to always include company size in the studies related to this subject.

In conclusion, it is important to remark also the effect on purely monetary performance.

For instance, Akter, Wamba, Gunasekaran, Dubey and Childe (2016) directly assess the interaction between the BD&IA capability and enterprise performance, proving evidences of a positive relationship between the two entities. In detail, "Big data analytics capability will have a positive impact on firm performance" is the tested hypothesis of the article.

This benefit of BD&IA is confirmed and evidenced also by other researches, such as the reports of Davenport and Harris (2007), Manyika (2011) and Barton and Court (2012), which respectively demonstrate the positive impact over profit maximization, sales and return on asset.

2.3.4 Challenges, Risks and Barriers to the Implementation

Once depicted the current situation regarding I4.0 definition and basic principles, which are the enabling technologies and all the achievable benefits and improvements, it is important to assess the related risks and drawbacks stemming from the adoption of SMTs.

In this sense, the classification made by O'Donovan, Leahy, Bruton and O'Sullivan (2015) perfectly depicts the possible barriers that a company can face in embracing I4.0:

- *Historical investment in ICTs and automation*: facilities may be unwilling to substitute old machinery which has received a significant investment in the past;
- *Regulatory and quality constraints*: internal and external regulations and/or standards may affect and hinder the adoption of SMTs in some industries;

- *Dependency on proprietary systems or protocols*: the adoption of new breakthrough technologies may be difficult, or even impossible, when a facility is locked-in to proprietary and closed technologies, instead of relying on open standards;
- *Weak vision and commitment*: the involvement of top managers is necessary, as leadership must drive the change; if this does not happen, facilities may not have the willingness to replace the existing technologies with something new and unknown;
- *High risk and disruption*: the possibility of achieving results different from the expectations is always existing, thus the desire to undertake a I4.0 project may remain weak, if it is not strictly necessary to survive in the market;
- *Skills and technology awareness*: the embracement of the new technologies and methods is a crucial requirement to implement SMTs, since it is necessary to shift from the existing approaches of the firm;
- *Multi-disciplinary workforce*: the decision-making process may need knowledge from different domains, thus multi-disciplinary personnel is fundamental to correctly implement SMTs.

The authors finally state that, obviously, the severity of a given risk may vary from case to case, and other obstacles may arise in the future. Moreover, the difficulties may be different also from facility to facility: in particular, the authors differentiate between greenfield sites, where the impediments should be not so relevant, and brown field sites, where the change is more difficult to be put in practice.
Other studies have tried to examine the obstacles to I4.0, coming approximately to the same conclusions of O'Donovan et al. (2015). For instance, Helu, Morris, Jung, Lyons and Leong (2015) underline the crucial role of experts, the fundamental contribution of training and the need for standards to exchange information. Beyond that, the paper identifies also in the loss of intellectual property a relevant risk. In order to tackle and overcome all these issues, the authors suggest to outline the situation by generating a risk assessment framework, in order to have a clear picture of all the involved risks.

The extant literature gives a remarkable importance also to the social consequences of I4.0. As Kang et al. (2016, p. 111) explain, "Manufacturing is a future growth engine that aims for a sustainable growth via management and improvement of the existing major manufacturing factors, such as productivity, quality, delivery, and flexibility based on technology convergence and various elements over societies, humans, and environment". The sentence shows how the implementation of SMTs has effects also over socio-cultural and sustainability aspects.

This concept is underlined also by Tortorella et al. (2020), which affirm that I4.0 technologies affect not only the technical and operational features of a company, but also the sociocultural ones. In accordance to that, Oztemel and Gursev (2018, p. 3) stress the necessity of having the capability to make machines communicating with human operators, which needs "a philosophical change in setting up new manufacturing facilities and a new workforce profile".

In sum, it is vital to ensure that the organizational structures and manufacturing infrastructure are ready to grasp new opportunities and values created by I4.0. Hence, both technological and cultural structures should support adoption and implementation of intelligent production systems (Fatorachian and Kazemi, 2018).

2.4 Literature Gaps

Once illustrated the literature findings, the main gaps emerged from the review which the thesis aims at filling are highlighted here.

The section firstly discusses the research gaps related to SMTs; then, the focus shifts ambidexterity; finally, the main gap – i.e. the absence of empirical studies regarding the influence of SMTs on exploitation and exploration within the organizational contest – is assessed.

I. Growing attention is being paid to the I4.0 concept. However, even if the positive impact of embracing I4.0 over IP and BP is widely investigated (Dalenogare et al., 2018; Brettel et al., 2014; Jeschke et al., 2017), there is a lack of works which assess the inverse relationship – i.e. the enabling effect of monetary performance over SMTs' adoption. In detail, it is not clear how much the implementation of SMTs within a company is affected by its ability in performing well, from a monetary viewpoint. As noted by many scholars (e.g. Lin and Chen, 2012), the adoption of such technologies can be very costly and, thus, it is intuitive to suppose that firms should perform well in order to be able to implement them. Companies should ensure the right level of investment in digital asset in the same way they do for other assets (McKinsey, 2015); anyway, no investigations on what enables these investments have been carried out.
   This represent a huge gap since it is important to understand which factors allow companies to be in a favourable position to implement SMTs and embrace I4.0;

II. Several authors, in analysing the consequences of ambidexterity, describe it as generic balance between exploitation and exploration (Lavie et al., 2010). This is especially true for papers which investigate IP, since the vast majority of them models ambidexterity as an interaction effect between exploitation and exploration strategies, without defining how companies should behave in order to simultaneously put in practice such approaches. For instance, He and Wong (2004) recognise that their study does not address the issue of which organizational design principles are appropriate for ambidexterity.
    Many scholars have argued that, if an enterprise wants to excel in both improving existing products and generating new product, it should apply structural ambidexterity (Levinthal and March, 1993; Gibson and Birkenshaw, 2004; Raisch and Birkinshaw, 2008); anyway, no one has clearly demonstrated that structural separation positively influences IP. On the contrary, a study proves the opposite: Zaidi and Othman (2015), by comparing contextual and structural ambidexterity, certify that the latter has no significant effect on new product development performance. However, this study has remarkable limitations: it does not have a critical perception of structural and contextual ambidexterity, since data are gathered in a subjective way, according to respondents' perception. On the contrary, a valuable study is produced by De Visser, de Weerd-Nederhof, Faems, Song, Van Looy and Visscher (2010), who analyse how different organizational structures suit with the incremental or radical product development processes. At the same time, through their analyses of the different structures' impacts, they indirectly indicate that organizations might benefit from adopting structural ambidexterity.
    Since the contextual ambidexterity has caught the attention of a high number of scholars, the lack of studies regarding structural ambidexterity and IP is an important gap that must be filled;

III. The review of extant literature has shown an almost complete absence of researches that simultaneously consider SMTs and ambidexterity in the intra-organizational context. Even if several papers evaluate the consequences of ICTs on ambidexterity (Xue et al., 2012; Lee et al., 2008; Revilla et al., 2007), only recently some authors have begun to investigate the SMTs' effects on firm's ambidextrous strategy. Specifically, two papers get close to this.
    Gastaldi, Appio, Corso and Pistorio (2018) analyse, with a case study, how digital technologies can help healthcare organizations and improve the exploration-exploitation paradox over time. However, as the authors underline, this exploratory study is difficult to

generalize, since it is focused only on hospitals and the healthcare system and it does not rely on empirical results.
Im and Rai (2013), contrarily, rely on an empirical analysis. However, they consider contextual ambidexterity, and examine two types of information systems as fundamental aspect of interorganizational relationships: operations support systems and interpretation support systems. As a result, they empirically prove that these types of systems are both enablers of contextual ambidexterity. Nevertheless, this study supports a contextual configuration of ambidexterity and investigates interorganizational relationships, expanding the unit of analysis outside the companies' boundaries.
As a consequence, these two papers clearly are not enough to affirms that SMTs are a possible enabler of ambidextrous' strategies, considering the intra-company context. Hence, a deeper analysis is required to shed lights on this interesting relationship.

3. METHODOLOGY

Starting from the gaps emerged during the literature review, this chapter illustrates: (i) the main objectives of the work; (ii) the methodology followed to develop the review of the literature; (iii) the theoretical model and the hypotheses tested and (iv) the procedures implemented to support the empirical analysis – i.e. data collection, preparation and analysis.

3.1 Objectives and Steps of the Work

3.1.1 Objectives

This sub-section presents the research questions that the thesis aims at answering.

The literature review has highlighted the lack of a study that empirically analyses the impacts of SMTs on one company possibility to simultaneously be exploitative and explorative, as pointed out in section 2.4.
Hence, the first question is:

RQ1: Do SMTs allow company to be ambidextrous, and thus pursue at the same time exploitative and explorative strategies?

Research question 1 enables a comprehensive analysis of the relationships between SMTs and companies' capabilities of simultaneously exploiting their operations and exploring their innovation potentialities.
This work questions the plausible influence that SMTs could have on organizations' operations, and thus the possibility to increase the efficiency related to automatic and flexible production system, which aims also at facilitating communication among parts, products, and machines (Lu, 2017). Given the possibility to generate more flexible, dynamic and intelligent plants by following I4.0 principles (Roblek et al., 2016; Qu et al., 2019), it is interesting to understand if this could positively influence companies' exploitation.
In the same way, the study examines the challenging impact that SMTs could have on enterprises' innovation function and the possibility to enhance exploration according to the large amount of data gathered. I4.0 aims monitoring and controlling the equipment by collecting a great quantity of data (Dalenogare et al., 2018), which can be reused in a proactive way to improve organizations' innovativeness. In this sense, one of the greatest challenges of SMTs is how to efficiently capture and manage machine-generated data in order to transform them into valuable information (Brousell et al., 2014). Therefore, it is interesting to check if SMTs alone

are enough to enhance enterprises' exploration, since the use of BD&IA forces companies to go through fundamental changes, sometimes also establishing dedicated units for analysing data, which can lead to some difficulties or complications.

The review of the extant literature has shown also the absence of works that simultaneously certify the beneficial effects produced by exploitation, exploration and structural ambidexterity on IP.
Hence, the second research question is:

RQ2: Do exploitation, exploration and structural ambidexterity have a positive impact on IP?

Research question 2 refers to explaining, through a unique model, which are the effects on the three aforementioned aspects on IP. As stated in literature gaps, no prior studies examine structural ambidexterity as a way to improve IP. Moreover, several investigations assess the relationship between exploitation, exploration and ambidexterity within the same model, but the results are contradictory: some authors (e.g. Katila and Ahuja, 2002; Nerkar, 2003) prove positive returns associated to ambidexterity; others (e.g. Atuahene-Gima, 2005; Li et al., 2010) demonstrate that being both exploitative and explorative is not effective, due to difficulties in managing such different strategies.
This work has the goal of clarifying this and determine if, combining exploitation within the operations function and exploration within the innovation function, companies can increase their IP.

The third and last question is a direct consequence of the analysis carried out by Piening and Salge (2015), who assessed the relationship between IP and monetary BP.
Hence, the third question is:

RQ3: Are well-performing companies, from a financial perspective, in a good position to have greater IP?

Piening and Salge (2015) demonstrate that innovation activities positively influence firm financial performance, and suggest future investigation on the reverse relationship, since it is equally plausible that it holds true. Several papers underline the positive effect of innovation over BP (e.g. Gunday, Ulusoy, Kilic and Alpkan, 2011), highlighting that innovation allows organizations to effectively tackle environmental changes and thereby improve the performance (Damanpour, Walker and Avellaneda, 2009), by creating competitive advantages difficult to be achieved by competitors (Bayus, Erickson and Jacobson, 2003). Anyway, innovation is strongly affected by exogenous factors (Kostopoulos, Papalexandris, Papachroni and Ioannou, 2011), so it is interesting to test whether firms which have financial availability could be more innovative, according to higher confidence as a consequence of more flexibility and protection in case of failure (O'Brien, 2003).

Therefore, this work aims at investigating a very low studied relationship understanding if companies with good financial performance are in a favourable position to increase their innovation ones, answering to the paper by Piening and Salge (2015).

3.1.2 Steps of the Work

Once presented the research questions and, thus, the objectives of the thesis, it is important to define the process followed in order to identify these questions and then provide an answer to them.

All the process' steps are illustrated in Figure 4.

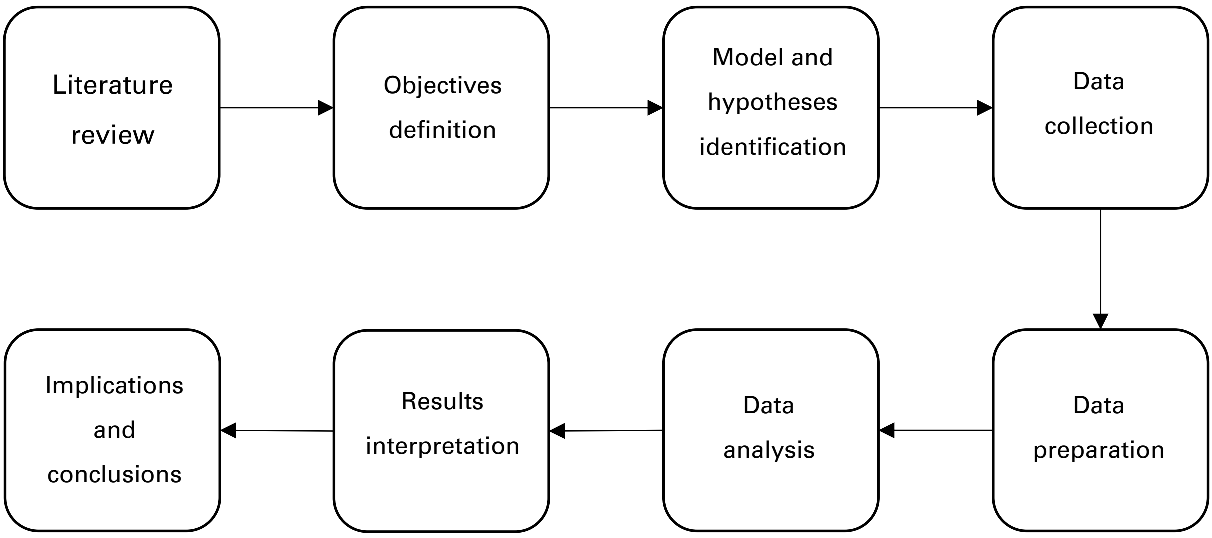

Figure 4: Steps of the research

First of all, this work relied on preliminary studies, essential to define the research questions and set up the model. The steps followed are detailed below.

- *Literature review*: a detailed analysis of extant literature regarding ambidexterity and SMTs has been carried out to identify the potential gaps. In particular, three lacunae emerged:
    - I. Absence of clear evidence about the I4.0's antecedents, especially the ones related to monetary performance;
    - II. Lack of papers that positively associate exploitation, exploration and ambidexterity to IP;

III. No investigations that empirically asses SMTs as antecedents of structural ambidexterity in the organizational context.

This step has been crucial to support the conducted work not only in the first stages, but also across all the subsequently developed phases;

- *Objectives definition*: once found the gaps not covered by the literature, the research questions have been formulated, along with the objectives that the thesis aims to fulfil. Specifically, the purpose is to clarify if ambidextrous strategies can be enabled by the adoption of SMTs, if these strategies positively influence the IP, and if well-performing firms are able to achieve higher IP.

Once identified the gaps and the research questions, the theoretical model to be tested with the empirical analyses has been generated. The steps followed are detailed below.

- *Theoretical model definition*: in order to answer to the questions, a model has been generated. In detail, the model is made up by six constructs and two control variables;
- *Hypotheses' formalization*: the theoretical model is supported by a set of hypotheses, which represent the relationships – i.e. the arrows – within the model itself. In practice, the proposed model is based on six hypotheses, that are empirically and statistically tested in order to be demonstrated.

Afterwards, the data have been gathered and later cleaned, in order to have the dataset ready for the statistical analyses. The steps followed are detailed below.

- *Data collection*: in order to collect the data, this work reaps the benefits of a survey emitted in 2016 by the Continuous Innovation Network (CINet) – with the aim of analysing the performance of 370 manufacturing companies;
- *Data preparation*: two fundamental procedures have been implemented to have a reliable database to test the model:
    I. Data reduction: the whole dataset has been reduced in order to have only the observation and items relevant and useful for the analysis;
    II. Data validation: elimination of some observation to solve the issues related to incomplete or noise data.

Later, with the support of Stata software, the empirical analyses have been conducted to prove the hypotheses. The steps followed are detailed below.

- *Exploratory factor analysis*: in order to build the constructs, this statistical analysis has been performed to find the most significative items for each construct. For this phase, a crucial role has been played by Cronbach's alpha, a coefficient which assesses the internal consistency of the retained factors;
- *Model testing*: using the SEM and checking the p-value to assess the validity, the final model was fitted using the maximum likelihood technique;
- *Overall model fit*: this step has allowed to assess the goodness of the overall fit of the model; three indicators was used for this purpose namely: Coefficient of Determination (CD), Root Mean Square Error of Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR).

After the statistical analyses, the study proceeded with the final phase, which consisted in explaining the results and their real implications. The steps followed are detailed below.

- *Result presentation and discussion*: the outcomes of the statistical analyses have been examined from a theoretical point of view in order to find interesting insights from the analyses;
- *Theoretical and managerial implications*: the observations of the previous steps have been finally translated into the real context in terms of contribution for the academic literature and recommendations for the decision-makers of firms;
- *Conclusions*: all the possible limitations and future extensions have been assessed.

3.2 Literature Analysis

This section has the objective to illustrate the methodology and the criteria adopted to conduct the literature review.

The review of the extant literature had two principal scopes: first of all, it illustrated a detailed overview of the existing academic findings related to the main topics investigated; second, it identified the literature gaps. As a result, it has been possible not only to describe in an exhaustive way both ambidexterity and SMTs, depicting their characteristics, benefits and drawbacks, but also to develop the questions and the framework of the study.

The research has been carried out through search engines – i.e. Google Scholar, Scopus and ISI Web of Knowledge -, selecting the adequate material from the most influential academic journals[1], without neglecting the importance of other sources – e.g. books, reports and conference papers, etc.

A precise timeframe for the considered academic productions has not been set, since the variety of topics investigated implies a wide time window to be examined.

Entering into detail, the review process has been performed as follows:

I. The analysis began with the investigation of exploitation, exploration and ambidexterity; thus, these three keywords represented the starting point of the research, also linking them to other expressions such as "organizational structure", "learning process" and other different organizations pillars;
II. Once developed an overview about the characteristics of the these concepts, their possible antecedents and the effects over performance – both monetary and technological – have been addressed; in doing that, search strings were applied, merging exploit, explore and ambidexterity with generic terms – e.g. "enablers", "antecedents", "effect", "positive interaction", etc. – or with specific ones – e.g. "ICT", "slack resources", "benefits of new product development", etc.;
III. A similar process has been carried out for the SMTs, aiming to realize a general analysis of I4.0, its objective and its fundamental technologies; for this reason, it has been applied not only a generic string – e.g. "I4.0", "Smart factories", "SMTs' goals", etc. -, but also the specific manufacturing technologies – e.g. "3D printing", "cloud manufacturing", etc. – has been used as keyword;
IV. Finally, even for SMTs, in order to have more complete and accurate findings, search strings like "I4.0 benefits", "SMTs' effects", "SMTs' risk and barriers" or "I4.0 challenges" have been used.

In parallel, also the papers quoted in the most relevant articles have been examined, providing a remarkable support to the study. These papers have been red to investigate the literature masterpieces and to focus the attention also on the main authors. Therefore, the literature review has been extended also to works not directly accessible through keywords or absent within the three used platforms.

A multitude of possible papers have been found and, in order to skim and select the most suitable between them, the following process has been carried out for each step of the

[1] The journal quality has been checked through the "Classification of relevant scientific journals" by Associazione Italiana Ingegneria Gestionale (2018, April)

aforementioned list.

The abstract of all papers found have been analysed, in order to discard researches not aligned with the purpose of this study. After that, the retained papers have been primary red and then classified in a systematic way, by developing a framework, where authors, journal, year, methodology adopted – e.g. literature review, survey, case study, etc. -, main results and personal observations have been recorded to have a formal, brief and standardized review of the knowledge.

Following this process, a total of 186 academic references have been treated and thus cited in the thesis.

3.3 Overall Model

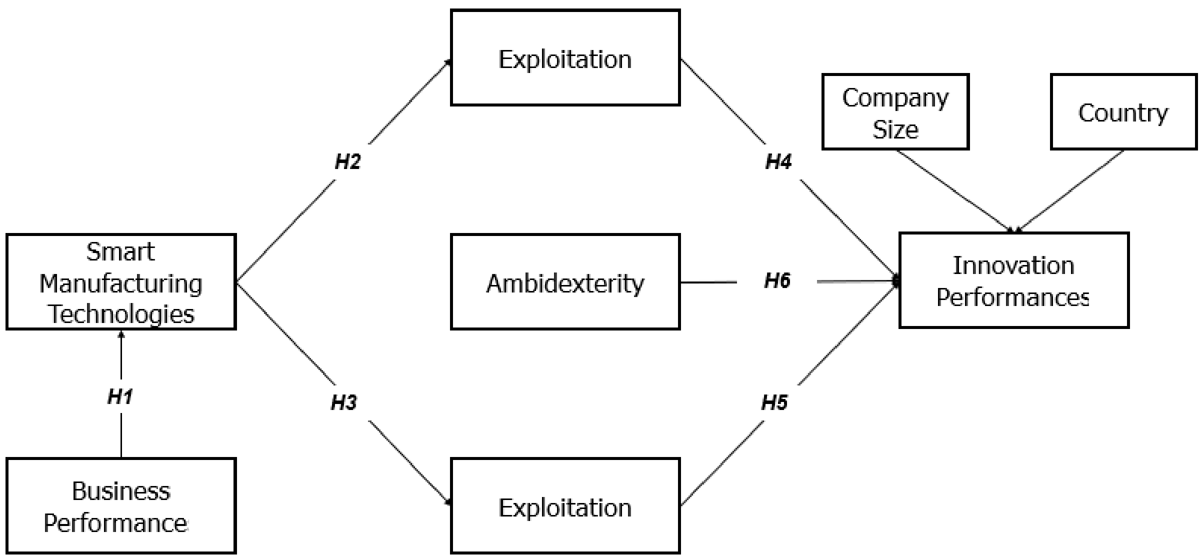

Figure 5: Theoretical model proposed by this research

In order to answer properly to the above-mentioned research questions, the conducted work relies on a model which incorporates six hypotheses, as depicted in Figure 5.

This model, in turn, is based on two concepts:

- *Constructs*: the key components that must be properly defined and deeply explained to allow an easy interpretation of their meaning;
- *Model's architecture*: the underlying theory that supports the model and connects all the constructs between them.

The underpinning principle of the study is to incorporate insights coming from different literature streams; indeed, by linking them, it aims at developing a deep understanding on how

companies with good BP should invest, and how these investments enable to be both exploitative and explorative, directly affecting their IP.
In detail, the analysis takes inspiration by the paper of Piening and Salge (2015). The authors demonstrate that innovation activities positively influence firm financial performance and suggest future investigation on the reverse relationship, since it is equally plausible that it holds true. Therefore, this thesis investigates how companies with good financial performance can increase their innovation ones, contributing to answer to the mentioned paper. Additionally, according to the principal research question, the effect of ambidexterity as mediator of the relationship is assessed. Specifically, 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, whereas the latter to exploration.

However, ambidexterity is not the only mediator inserted into the model, since also the SMTs are taken into consideration. It is well-known that the interesting breakthrough innovations of I4.0 are revolutionizing the companies' way of doing business; however, they represent a complex type of innovation, which relies on expansive technologies. Therefore, the purpose is to verify whether good financial performance facilitate and foster the adoption of SMTs, because firms that own financial slacks are protected in case of failure, and thus they can easily invest (O'Brien, 2003).
Moreover, the model aims to empirically investigate the relationship between SMTs and exploitation and exploration, thus also ambidexterity, within the organizational context.
The hypothesis that technologies can enhance exploitation or exploration is already addressed by some authors, like Xue at al. (2012), who show that ICTs asset could be designed toward exploitation processes for efficiency or exploration processes for innovation. However, since SMTs should enable a "fully-integrated and collaborative manufacturing system that answers in real time to meet the changing conditions in the factory, in the supply network, and in customer needs" (Thompson, 2014), the proposed model considers exploitation only in the operations domain. On the other hand, exploration is examined under a technological lens, in order to understand if the SMTs' role in enhancing collection and exchange of data acquired by smart sensors and in enabling BD&IA (Kang et al., 2016) has the capability to improve company exploration, creating innovative technologies and new markets (Lubatkin et al., 2006).

Finally, the model aims at determining the role of exploitation and exploration and their interaction effect – i.e. ambidexterity – on IP. This goal stems from the conflicting opinions emerged by reviewing the extant literature, as scholars do not accurately clarify neither the effects of exploit and explore over IP, nor the one of ambidexterity over such performance. The first two relationships are sometimes modelled as inverted U-shape, since exceeding in one of the two strategies creates adverse results: too much exploitation increase rigidity, which impede to be competitive in the long-term (Wang and Li, 2008); too much exploration generates plenty of unfamiliar insights that can neutralise the benefits provided (Li et al., 2010). Nevertheless, other authors, like Atuahene-Gima and Murray (2007), suggest that, as new ventures increase their exploitation or exploration, they become more efficient, positively influencing their IP, proving that assumption of weaken returns associate to high level exploitation could be overblown.

Moving on to the third relationship – i.e. ambidexterity-IP -, scholars suggest that ambidextrous companies have the capabilities to manage these two divergent processes and thus enhancing their competitiveness (O'Reilly and Tushman, 2013). Anyway, as argued by Atuahene-Gima and Murray (2007), it is more suitable to couple high (low) exploitation with low (high) exploration, since a high-high combination create tension in the competition for scarce sources. Therefore, the model aims at solving this debate and hypothesizes a positive relationship between ambidexterity and IP.

Table 5 helps to better understand the theoretical meaning which underpins the proposed model:

CONSTRUCT NAME	**DEFINITION**
Business Performance	The financial performance of the company compared to competitors' ones
Smart Manufacturing Technologies	The level of adoption of SMTs within the company
Exploitation	The operations' exploitation level within the company, assessing the processes adopted within the production function
Exploration	The innovation' exploration level within the company, assessing the processes implemented within the innovation function
Ambidexterity	The ability to pursue, at the same time, operations' exploitation and innovations' exploration, thus investigating how much the company is structurally ambidextrous
Innovation Performance	The innovation level of the company compared to competitors' ones

Table 5: Definition of the constructs

In addition to these constructs, two control variables are examined: company size and country. Their selection is a consequence of the literature review process.

The first one, which tackles the size issue, is introduced since many authors theorised probable difficulties for SMEs in being ambidextrous. For instance, Ebben and Johnson (2005) prove

that small organizations would have scarce performance in case they seek to pursue both exploitation and exploration. Voss et al. (2008) argue that structural ambidexterity suits large firms but not the small ones. Nevertheless, as Jansen et al. (2009) affirm, large firms may possess resources that can be allocated to the simultaneous realization of contradictory activities but, on the other hand, they could also lack sufficient flexibility to adopt ambidextrous behaviour.
Therefore, it is appropriate to check the effect of size over the possibility to achieve great IP.

The second one is included considering the demographic dispersion of survey's respondents, in order to understand if there are some misalignment according to the country of origin of the enterprises. This because each different country has its own environment and dynamism which can influence companies' behaviours, decision and performance. Additionally, Erthal and Marques (2018) verified that different socio-economic contexts influence the responses. For these reasons, it is correct to check also the possible misalignment stemming from the country where the different firms are operating.

3.4 Hypotheses Generation

The theoretical model paves the ways to the generation of the hypotheses that are tested in this work. All of them represent a critical relationship within the proposed model and are deeply illustrated and described in the following sub-sections.

3.4.1 Effect of Financial Performance on Smart Manufacturing Technologies implementation

The belief to be proved is that companies able to achieve good financial performance are well-positioned to carry out investment, and have the possibilities is to invest in SMTs, since the adoption and implementation of these technologies can be very costly (Lin and Chen, 2012). As explained in the literature review, there are no studies that analyse the relationship between good financial performance and the adoption of SMTs, and few support is given to the idea that higher investments are triggered by positive financial indicators.
Müller, Kiel and Voigt (2018) argue that I4.0 implementation should be designed specifically for the organization and this is particularly challenging for enterprises without enough financial resources.
The literature suppose that positive financial results can increase the availability of resources, as Sharfman, Wolf, Chase and Tansik (1988) hypothesize that firms performing better should

have higher levels of available assets. Singh (1986) conceptualize these resources as a result of organizational success.

Empirical evidence regarding the influence of high performance over the possibility to have slack comes from Chakravarthy (1986). From the literature it comes also the evidence about the slack resources' effect, as they provide the companies a great level of money to invest (Wu and Tu, 2007). As already said, they are the ones not consumed by the necessity of enterprise's daily operation and they enable organizations to have the possibility to focus on expansive innovative ventures (Nohria and Gulati, 1996). For this reason, firms need a certain amount of these resources if they want to invest in SMTs, since such technologies are characterized by costly spending. Indeed, firms that own financial slacks can easily invest, because they protect organization in case of failure for depletion of resources (O'Brien, 2003).

Lee and Wu (2016) note how in the past studies have shown that financial availability encourage not only experimentation and risk taking, but also exploitation opportunities.

According to Greve (2003), well-performing companies are more likely to own extra resources that can increase their propensity to engage in costly innovation activities, as SMTs can be classified.

In the discussed theoretical model, the mediating effect of financial slacks is not taken into consideration, as enterprises which perform well should produce the resources needed to carry out investment, so they should have the possibility to implement SMTs within their organizations.

Basing on these arguments, the next hypothesis follows:

HYPOTHESIS 1: Good financial performance of a company positively influences its potential implementation of SMTs.

3.4.2 Effect of Smart Manufacturing Technologies on Exploitation

Several authors model ICTs as one antecedent of exploitation: for instance, Stein and Zwass (1995) develop the idea that ICTs adoption can support the acquisition and exploitation of knowledge practices; moreover, Malhotra (2001) proposes that ICTs systems are enablers of exploitation. Supporting this concept, Xue et al. (2012) demonstrate how, at lower levels of environmental complexity, the primary role of the ICTs asset portfolio is enabling exploitation to enhance efficiency. Also, Kane and Alavi (2007) prove the positive effect of ICTs on exploitation, arguing that appropriate tools are the ones characterized by a rapid homogenization of knowledge.

From all these contributions, it comes the idea that companies able to implement SMTs can improve their operations' exploitation capabilities. As stated in the literature gap analysis, there is no empirical study which investigates this relationship; anyway, similar findings suggest that, usually, the initial objective of enterprises which undertake a digital transformation is exploiting more effectively their resources and achieving efficiency in term of time savings, cost reduction or managerial simplification (Gastaldi et al., 2018). Authors also affirm that digitising assets is a short-term strategy that requires a low use of digital capabilities, and thus it can easily improve exploitation. Moreover, considering SMTs' benefits from the operational perspective, they lead to the optimization of the time-cost trade-off, reducing resource utilization and increased energy savings (Ali and Azad, 2013). For instance, focusing on additive manufacturing, Kang et al. (2016) affirm that the possible advantages of this technology are represented by materials and resources' efficient utilization.

Since exploitation's essence is the refinement and extension of existing competences and technologies aiming at reducing variation and increase efficiency (March, 1991), considering the aforementioned SMTs' gains and the evidence that ICTs can be an antecedent of exploitation, companies which implement SMTs should easily exploit their operations.

Basing on these arguments, the next hypothesis follows:

HYPOTHESIS 2: The adoption of SMTs has a positive influence on operations' exploitation strategies.

3.4.3 Effect of Smart Manufacturing Technologies on Exploration

Once companies are able to reach the main benefits of initial digitisation investments, the introduced digitisation systems allow the exploration of new and radical ways of providing product or services (Gastaldi et al., 2018). This is related to the organizations' desire of exploring new ways of extracting value from previously digitised data.

SMTs are included in the ICTs, which are accepted as a way to organize and synthesize information, increasing the quantity and the quality of knowledge, information and ideas which an organization can access at low expense (Revilla et al., 2007).

This happen because, once firms learn how to deal with data, they can reach the last phases of the process purposed by Dai et al. (2019), namely using the data to perform predictive and prescriptive analytics. These phases are a crucial step of I4.0 and allow companies to adopt proactive approaches, anticipating the future and easily increasing their possibility to explore future trends. Anyway, even if enterprises are not ready to adopt a proactive approach, also the reactive one can generate great benefits because, as Sambamurthy, Bharadwaj and Grover (2003) argue, ICTs enable companies to quickly react to changes in market conditions by supporting strategic adjustments when necessary. Moreover, ICTs capability is expected to improve data collection and processing and thus allowing organizations to respond to market changes in timely manner and identify new business opportunities (Chaudhuri, Dayal and Narasayya, 2011); this is also the reason behind Soto-Acosta et al. (2018) findings, which demonstrate that aligning ICTs resources with other critical resources could enhance firms' exploration capability.

Following these demonstrations and the goals of I4.0, companies should improve their exploration orientations thanks to the implementation of SMTs.
Basing on these arguments, the next hypothesis follows:

HYPOTHESIS 3: The adoption of SMTs has a positive influence on exploration strategies within the innovation function.

3.4.4 Effect of Exploitation on Innovation Performance

The knowledge developed over years indicates, with a general consensus, that exploitation enhance short-term performance; in this sense, Atuahene-Gima (2005) demonstrate that exploitation increases incremental innovations since it is focused on productivity improvements and variance reductions. Some authors, however, reveal the positive exploitation's effects on both short-term and long-term IP – i.e. continuous improvement and radical innovation. For instance, Nerkar (2003) proves that, higher the exploitation, greater its impact on knowledge creation; at the same time, the author does not find support for the hypothesis of decreasing returns associated to high level of exploitation. Another evidence comes from He and Wong (2004), which show that exploitation has a positive effect on product innovation intensity, without supposing or finding any negative counterindication.
According to Benner and Tushman (2002), exploitation orientation is focused on improving efficiency and reducing variance; for this reason, it is plausible to assume that firms which follow an exploitation strategies for their operations should for sure enjoy direct and visible consequences over their IP, due to more suitable processes.
Lee, Lee and Garrett (2017) support this concept, demonstrating that exploitation orientation increases the process innovation's likelihood, contrasting the theory that exploitation could lead to "success trap" (Levinthal and March, 1993), impeding companies to be competitive in the long-term (Wang and Li, 2008).

However, firms developing exploitation strategies are able to easily reach economies of scale and scope, thus they will increase IP (Auh and Menguc, 2005). Atuahene-Gima and Murray (2007), finding a U-shape relationship between these two aspects, suggest that, as new ventures increase their exploitation, they become more efficient in their learning processes, and this positively influence their IP,

As a consequence, by focusing on operations' exploitation, firms which have both the Chief Operating Officer (COO) and the Chief Technology Officer (CTO) roles should be able to innovate without suffering rigidity, typically associated to exploitation, since the innovation unit should diminish the probability of rigidity issues, caused by an excessive operations' exploitation.
Basing on these arguments, the next hypothesis follows:

HYPOTHESIS 4: The level of operations' exploitation within a company has a positive influence on its overall IP.

3.4.5 Effect of Exploration on Innovation Performance

Atuahene-Gima and Murray (2007) and He and Wong (2004) analyse the relationship between exploration and IP, discovering that the same results and comments found for exploitation-IP relationship can be applied in this case.
According to its dynamics, the literature links exploration only with long-term performance, since it concerns innovative concepts which imply uncertain and distant return (March, 1991). Nerkar (2003) demonstrate that, the higher the exploration, the greater its impact on knowledge creation; however, the author validates also the hypothesis of decreasing returns associated to high levels of exploration, thus illustrating an inverted U-shape relationship. In this sense, Li et al. (2010) determine that too much exploration is associated with harmful results, since a large amount of new knowledge generates plenty of unfamiliar insights that can neutralise the benefits provided.
Anyway, pursuing explorative strategies within the innovation function allow companies to embrace breakthrough innovations, expanding and enriching the organizational knowledge base; as a consequence, enterprise's market, along with environmental changes' perception, would be reinforced, giving managers the possibility to seize the right opportunities and improve the management of innovation (Wang and Lam, 2019). For this reason, it can be supposed that companies pursuing exploration strategies within the innovation function will easily benefit from large amount of new knowledge's introduction. This because innovation

function's nature is related to managing changes and fostering the enterprise's ability to undertake radical innovations.

In a similar vein, even if Katila and Ahuja (2002) argue for decremental returns associated to high level of exploitation – i.e. inverted U-shape – the statistical analyses show a positive, linear relationship; Yalcinkaya, Calantone and Griffith (2007) certify that exploration has positive effect on incremental and radical IP, and exploration capabilities foster product innovation. Continuing on this, Lee, Lee and Garrett (2017) prove that exploration orientation positively affects incremental and radical product innovation.

According to the aforementioned concepts, exploration should have a beneficial impact on overall IP.

Basing on these arguments, the next hypothesis follows:

HYPOTHESIS 5: The level of innovation's exploration within a company has a positive influence on its overall IP.

3.4.6 Effect of Structural Ambidexterity on Innovation Performance

Starting from the definition given by Raisch and Birkinshaw (2008), ambidexterity is identified as the capability to simultaneously conducting today's business efficiently and being able to answer environmental changes. This because ambidextrous companies mix exploitative innovation strategies, which bring predictable and positive results in the short-term, and explorative strategies, which impact in the long-term (Benner and Tushman, 2002).

Considering the different effects over performance, it could be supposed that, by balancing the two dimensions, the firm's overall IP would improve; indeed, as Hughes (2018) suggests, ambidextrous enterprises should be capable to simultaneously overcome the success trap – i.e. excess of exploitation – and the failure trap – i.e. excess of exploration. This insight is consistent with a broad stream of researches. For instance, Katila and Ahuja (2002) and Nerkar (2003) suggest that firms enhance their IP from pursuing both exploitative and explorative strategies – i.e. by being ambidextrous. Conversely, some authors underline how ambidexterity has negative effect (Atuahene-Gima, 2005), arguing that it is more suitable to couple high (low) exploitation with low (high) exploration, since an high-high combination create tension in the competition for scarce sources, according to the divergent nature of exploit and explore.

Kim, Song and Nerkar (2012) demonstrate that, if a firm needs to improve its innovative capabilities, it should reach an effective equilibrium between exploitation and exploration; this support the validity of the theoretical model of this research, which relies on a structural ambidexterity, as a result of operations' exploitation and innovation' exploration. In practice, the configuration proposed by the model is supposed to reduce the issues related to the divergent nature of the two strategies since it recognizes the differences across departments in terms of orientations (Golden and Ma, 2003), allowing the coexistence of conflicting mindsets (Pertusa-Ortega and Molina-Azorín, 2018). In this way, each of the two strategies can utilize its own organizational space (De Visser et al., 2010), showing how structural differentiation is supposed to be an effective solution to the ambidexterity paradox.

Following the reasons stated above, structural separation should be an adequate solution to achieve such balance, overcoming structural inertia and scarce benefits from accelerating exploitation (Levinthal and March, 1993).
Basing on these arguments, the next hypothesis follows:

HYPOTHESIS 6: The structural ambidexterity of a firm – defined as interaction of operations' exploitation and innovation's exploration -, has a positive influence on its overall IP.

3.5 Constructs Operationalization

Once presented the model and hypotheses, it is necessary to define which items have been used and how the constructs have been operationalized.

The variables have been defined not only basing on the literature analysis, but also considering the responses available from the data source of this thesis – i.e. the survey issued by the CINet -, which is illustrated in more details in the following section.

Table 6, Table 7, Table 8, Table 9 and Table 10 exhibit the items that constitute each construct of the proposed model.

CONSTRUCT	ITEMS	ADAPTED FROM	QUESTION
Business Performance	*BP_1*	McDougall and Tyers (1994)	Our average performance, in terms of net profit, relative to our main competitors over the past three years was…
	BP_2	McDougall and Tyers (1994)	Our average performance, in terms of return on sales, relative to our main competitors over the past three years was…
	BP_3	McDougall and Tyers (1994)	Our average performance, in terms of profit growth, relative to our main competitors over the past three years was…

Table 6: Items' origin and associated question of the survey for the construct BP

CONSTRUCT	ITEMS	ADAPTED FROM	QUESTION
Smart Manufacturing Technologies	*SMT_1*	Vázquez-Bustelo, Avella and Fernández (2007)	In our company, the degree of use of / Computer-aided process planning (CAPP) is…
	SMT_2	Vázquez-Bustelo, Avella and Fernández (2007)	In our company, the degree of use of Manufacturing resource planning (MRP II) / enterprise resource planning (ERP) is…
	SMT_3	Vázquez-Bustelo, Avella and Fernández (2007)	In our company, the degree of use Automatic identification / Bar code systems / RFId is…
	SMT_4	IMSS [2](2013)	In our company, the degree of use of "Smart" ICT applications supporting supplier/customer collaboration, connectivity (plants, equipment, robots, lines, workers), data processing (big data) / information mining, modelling/simulation is…
	SMT_5	IMSS (2013)	In our company, the degree of use of Advanced manufacturing technologies (e.g. water and photonics-based / Laser cutting, additive manufacturing / 3D printing, high precision technologies, micro/nano-processing) is…

Table 7: Items' origin and associated question of the survey for the construct SMT

CONSTRUCT	ITEMS	ADAPTED FROM	QUESTION
Exploitation	*EXPLT_1*	Atuahene-Gima (2005)	In our production function, we systematically invest in incrementally improved equipment, tools and techniques to improve the performance of our production processes
	EXPLT_2	Atuahene-Gima (2005)	In our production function, we systematically acquire state-of-the-art knowledge, skills, equipment, tools and techniques
	EXPLT_3	Kim et al. (2012)	In our production function, we systematically acquire new managerial and organizational skills that are important for production
	EXPLT_4	Atuahene-Gima (2005)	In our production function, we systematically strengthen and upgrade current knowledge and skills for familiar production processes and technologies

Table 8: Items' origin and associated question of the survey for the construct exploitation

CONSTRUCT	ITEMS	ADAPTED FROM	QUESTION
Exploration	*EXPLR_1*	Akman and Yilmaz (2008)	In our innovation function, we systematically support and encourage creativity, inventiveness and participation in product innovation and improvement
	EXPLR_2	Akman and Yilmaz (2008)	In our innovation function, we systematically invite and use feedback and ideas from external partners (customers, suppliers, research institutes) to improve our product development practices and performance
	EXPLR_3	Akman and Yilmaz (2008)	In our innovation function, we systematically adapt to changes in the competitive environment by innovating and improving our products
	EXPLR_4	Yam, Guan, Pun and Tang (2004)	In our innovation function, we systematically use clear project targets, project phase standards and project management regulations for our product development activities

Table 9: Items' origin and associated question of the survey for the construct exploration

[2] Instituto Mexicano del Seguro Social (IMSS) is a governmental organization that assists public health, pensions and social security in Mexico operating under the Secretariat of Health.

CONSTRUCT	ITEMS	ADAPTED FROM	QUESTION
Innovation Performance	*IP_1*	Atuahene-Gima (2005)	Our average performance, in terms of total new product development costs as a percentage of sales, relative to our main competitors over the past three years was
	IP_2	Pullman, Maloni and Carter (2009)	Our average performance, in terms of Employee performance on health and safety, quality of life, motivation and satisfaction, knowledge and skills, relative to our main competitors over the past three years was
	IP_3	Griffin and Page (1993)	Our average performance, in terms of project planning accuracy (e.g. percentage of projects over-running planned project lead time, time-to-market or budget), relative to our main competitors over the past three years was
	IP_4	----	Our average performance, in terms of launch of "smart" (digitalized, intelligent) products (with in-built sensors, microprocessors, memory) (Internet of Things and Services), relative to our main competitors over the past three years was

Table 10: Items' origin and associated question of the survey for the construct IP

Since ambidexterity represents the interaction between two other constructs of the model – i.e. exploitation and exploration -, its operationalization has been performed according to a different procedure, which does not directly refer to the survey and relies on Stata; more details on the operationalization of this constructs are illustrated in section 3.9.

3.6 Data Collection

In order to collect the data necessary to demonstrate the aforementioned hypotheses and answer to the proposed research questions, this thesis is based on a collaboration with the School of Management of Politecnico di Milano. In particular, this study reaps the benefits of a survey emitted in 2016 within the CINet with the aim of analysing the performance of manufacturing companies.

The target sample were the COOs and the CTOs of 370 enterprises located in eleven distinct countries – i.e. Austria, Brazil, Canada, Denmark, Hungary, Italy, Netherlands, Pakistan, Spain, Sweden, Switzerland – and operating in several different industries – e.g. automotive, apparel, food, beverage, etc.

The design of the survey has benefitted from already existing scales. In detail, the survey was structured into five main sections:

I. *Strategy*: aimed at assessing the general information, the strategy adopted and the performance achieved within the firm;
II. *Production*: aimed at assessing the resources available, the strategies adopted and the performance achieved within the operations department;

III. *New product development*: aimed at assessing the resources available, the strategies adopted and the performance achieved within the technology department;

IV. *Organization and culture*: aimed at assessing the culture and the level of centralization, connection and formalization within the organization;

V. *Context*: aimed at assessing the environment which the firm is operating in, considering the points of view of market, competition and technology.

The COOs were asked to answer to sections 1,2,4 and 5, whereas CTOs were asked to answer sections 1,3,4 ad 5.
Additionally, it is important to underline which typology of questions the survey comprehends:

I. *Multiple choice questions*: based on a Likert scale which goes from 1 (low/disagree) to 5 (high/agree);

II. *Open-ended questions*: mainly related to the general information about the firm included into the first section of the survey.

As a result, CINet obtained a dataset constituted by 560 observations since, in some cases, only one of the two officers filled in the survey.[3]

3.7 Data Preparation

Accurate and effective results of the data analysis can be achieved only when the inputs data are highly reliable. For this reason, it is necessary to clean and prepare the database before starting to examine it.

In particular, this section is structured as depicted in Figure 6.

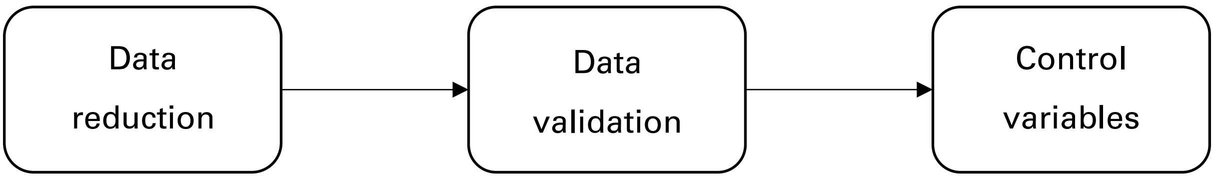

Figure 6: Steps of the data preparation phase

First of all, the dataset has been reduced according to the theory which underlies the proposed model. Afterwards, the obtained database has been cleaned and thus validated to find the items to be tested with the exploratory factor analysis during the data analysis phase. Finally, some

[3] For more details regarding the questions of the survey, see Appendix B

adjustments have been applied to include the control variables into the model.
The details are illustrated in the following sub-sections.

3.7.1 Data Reduction

Data coming from the survey were handled using the software Microsoft Excel.
In particular, each row represented a respondent, whereas each column referred to a question; this led to a starting raw matrix made up by 560 rows and 240 columns. However, it has not been necessary to consider the whole database provided by CINet; indeed, given the structure of the model discussed in this work, not all questions and responses have been deemed necessary to demonstrate the hypotheses and answer to the research questions.

In practice, two processes have been carried out during this phase, according to the different dimension of the dataset considered – i.e. rows or columns.
First, since this thesis investigates exploitation in the production domain and exploration in the technological one, both the production and the new product development sections of the survey were necessary to carry on a precise and correct analysis. As a consequence, only the companies that effectively answered to all the five sections have been taken into considerations – i.e. both the COO and the CTO filled in the survey -, leading to the transition from the initial raw database – made up by 370 firms and 560 observations – to a smaller one – formed by just 189 enterprises and 378 observations. It is important to underline that, with this procedure, all the firms operating in Austria and Netherlands have been excluded, since no one of them answered to all the sections of the survey; this reduced the number of countries to nine. Afterwards, the responses coming from the COO and the CTO of the same organization has been merged into a single observation, ending with a dataset of just 189 responses. In doing this aggregation process, it has been also necessary to calculate the average between the answers of COO and CTO to the questions in common – i.e. sections 1, 4 and 5 -, leading to a more accurate esteem of the real scenario of the firm.
Moving on to the other dimension of the starting database, the number of questions was set at 240. Fortunately, in order to support the hypotheses of the conducted work, not all the questions of the survey have been considered necessary. Indeed, by digging into the extant literature, it emerged that only a few sets of variables could be deemed adequate to generate the constructs of the theoretical model. For this reason, several columns have been immediately excluded from the analysis, leading to a reduction till 60 variables.

In sum, the original dataset has been reduced from a starting dimension of 560x240 to a final one of 189x60. This process of diminishing the magnitude of the data to be handled had a positive effect on the subsequent phases of the investigation, since it made the database more readable and it eased the SEM analysis with Stata.

3.7.2 Data Validation

In detail, this step of the data preparation phase aimed at tackling two main issues: incomplete data and noise data.

Concerning the former topic, incomplete data refer to the management of missing values – i.e. response not submitted by the respondents. The absence of some values has a great relevance since, in the factor analysis, even the observations with just one empty value are removed from the computation. Therefore, keeping into the dataset columns with several missing values is a completely wrong choice.

First of all, in order to overcome this obstacle, a preliminary step to check for zeros and empty values to ensure the correctness of missing values has been carried out. Then, a reduction of the dimension of the database has been implemented once again. In detail, the sixty remaining questions have been compared between them, from the model's constructs point of view, with the purpose of keeping only the ones with the lowest number of missing values. For instance, the construct "IP" could have been generated with thirteen different questions between the sixty available in the previously reduced dataset; by counting the number of missing values per column, it has been possible to exclude a priori nine questions between the thirteen available. Therefore, by doing this process for all the other constructs of the theoretical model, the number of columns was reduced from 60 to 23.

Moving on to the second topic of this sub-section, the term "noise data" consists in erroneous or anomalous values, usually referred to as outliers, which may generate inaccuracies in the analysis.

In order to tackle this possible issue, every row of the database has been examined to find some interesting pattern. By looking at the overall data, it emerged that some firms answered in a quite anomalous way, for instance by assigning 1 or 5 to all the twenty questions. Obviously, these observations have been excluded from the analysis in order to avoid some unexpected interference. As a result, the 189 respondents of the database have been reduced to 140.

Therefore, even in this phase the dimension of the dataset has been cut, generating a more compact and readable version of the results of the survey, made up just by 140 observations and 20 variables.

3.7.3 Control Variables

Before moving to the data analysis phase, a final step of the preparation was required.
As far as the theoretical model is concerned, two control variables have been included into the diagram: country and company size.
In order to deal with these additional elements, the following procedures have been put in practice.

Concerning the country, the starting point has obviously been the question related to the country of origin of each firm, placed in the first section of the survey.
This question generates a so-called "categorical variable", a qualitative parameter which can assume a set of distinct and not numerical values – e.g. Brazil, Canada, Denmark, etc.
However, it is not easy to manage such type of variable with the SEM path analysis in Stata; hence, this question has been transformed into a collection of dummy variables. This particular variable can assume only a value equals to 0 or 1, respectively meaning that an observation belongs or not to a given class. Considering the context of this research, it means that, if a firm is operating in Brazil, it will have a value equals to 1 in the dummy variable "Brazil", and a string of 0s in all the other dummy variables.
Additionally, it is important to underline that, as far as the categorical variables are concerned, it has been sufficient to include just eight dummy variables into the database; indeed, if a given firm has a value of 0 in all the eight new columns, it means that, by elimination, it operates in in the ninth country.

Moving on to company size determination, the implemented procedure is quite straightforward. In order to generate this new variable, the number of people working in the business unit and in the department have been summed. These two data were available in the answers to the first section of the survey.
It is clear that this sum is a proxy and it does not represent the correct firm size; however, this step has been necessary to overcome the lack of data regarding the real company size value. In doing this summing procedure, a particular attention has been given to the missing values: if at least one of the two addenda's datum was missing, an empty value has been assigned to the

variable company size.
At the end of this phase, the dataset was constituted by 140 observations and 29 variables.

3.8 Data Analysis

This section illustrates the methodology followed to carry out the statistical analyses once data collection and the data preparation have been detailed.
The process of examination is divided into two principal steps, according to the statistical technique applied: factor analysis, implemented to reduce the dimensionality of the worldwide dataset, and Cronbach's alpha, implemented to verify the robustness and the internal consistency of the constructs. Finally, the theoretical model has been tested and later slightly adjusted to better reflect the reality through the use of SEM, a statistical technique able to assess the relationship between different constructs – i.e. path analysis. The implemented steps are summarized in Figure 7.

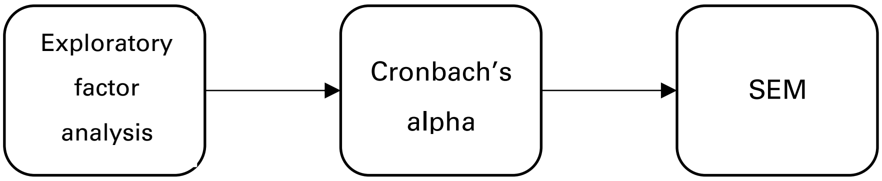

Figure 7: Steps of the data analysis phase

All these statistical analyses have been performed on Stata, a software package for data manipulation, management, exploration, analysis and graphical creation.
In the following pages, the above-mentioned methods and tools are discussed in greater details.[4]

3.8.1 Factor Analysis

Factor analysis is a statistical technique able to summarize a large number of variables of a dataset into new created factors, which are linear combination of the input variables. By leveraging on this tool, the complexity of the original database can be reduced without loss of significance (Kim, Ahtola, Spector and Mueller, 1978).
More specifically, factor analysis consists in two different techniques, which can be adopted according to the different context: exploratory and confirmatory factor analysis.
The former is a data-driven method (Kim, Ku, Kim, Park and Park, 2016) which aims at exploring possible underlying factor configurations of a set of variables without imposing a

[4] The entire code of Stata is illustrated in Appendix A

preconceived structure on the outcome (Child, 1990). On the other hand, the latter is a theory-driven method (Kim et al., 2016) which requires a strong and a priori defined theory underlying the measurement model, and tests whether the obtained dataset is suitable for it (Williams, 1995).

For the purpose of the analysis, the exploratory technique has been adopted to determine the structure of the constructs and thus generating them on the basis of the available data. Indeed, even if there is an existing underlying theory behind the model, no hypotheses related to constructs' configuration were previously formulated. Moreover, even if the items of the survey have been adapted from already existent questionnaires, the idea of this work is to arrange them in a different way.

Figure 8 illustrates the different procedures implemented over Stata.

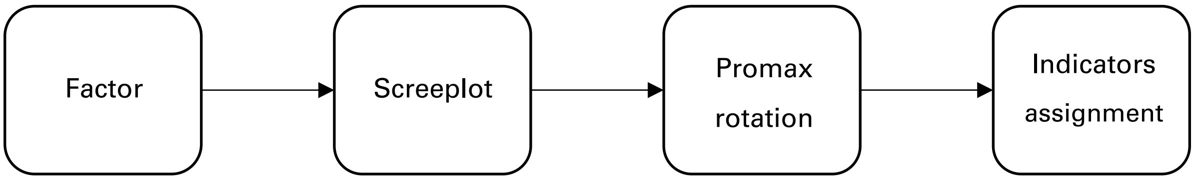

Figure 8: Procedures performed to generate the constructs

Going into detail, factors were first of all extracted through the "factor" default function; specifically, only those with an eigenvalue greater or strictly lower than 1 have been preserved. During this retention step, also the value of the cumulative variance explained by the factors and the screeplot has been observed, in order to optimize the outcome of the examination. After this process, the focus shifted to associating each variable to a unique factor.

First of all, the loading matrix was rotated by an oblique pro-max rotation; then, the loading indicators have been sorted to make the outcomes more readable and easier to be analysed. An indicator, in order to be assigned, should have a high load for the respective factor and a low one for the others. In practice, the indicators have been allocated to a specific factor only if the respective loading was higher, in absolute value, than 0.4.

Finally, also the uniqueness of each variable has been assessed, a measure which reflects the unique contribution of each item to explaining the variability inside the data matrix. Value higher than 0.6 are generally considered high; in case of a score above this threshold, the variable is probably not well explained by the factors. The complementary indicator of the uniqueness is the commonality, which is calculated as follows: $1 - Uniqueness$. These values are generally used to express the quality of the contribution of each item to the model.

Once concluded this fundamental process of exploratory factor analysis, the focus shifted on confirming and verifying the statistical validity of the generated factors.

3.8.2 Assessing the Reliability of Factors

Indicators assignment to each factor has been assessed and verified with the scale reliability coefficient, called Cronbach's alpha, which practically measures the level of internal consistency by showing how closely related a set of items is.

The values of this parameter can range between 0 and 1. A value close to 0 indicates that there is a low level of correlation among the items and it is impossible to generate a meaningful factor; a value close to 1 indicates that all the items measured contribute roughly equal and provide a valuable contribution in determining it.

Ideally, all the factors have a reliability close to 1; however, in the real applications, this hardly happens. Nunally and Bernstein (1978) proposes a reliability of 0.9 as a minimum which can be accepted. However, several other authors underline how a value equal or higher than 0.9 is considered to be excellent, and a value between 0.7 and 0.9 is considered to be good and acceptable (Kim et al., 2016). For this reason, in this work all the factors with a value of alpha higher than 0.7 have been deemed admissible.

In case of a very poor score – i.e. lower than 0.6 – the indicators assignment was repeated, and those with the lower loadings have been excluded from the analyses. In case of a score slightly lower than 0.7, the theoretical relevance of the item with the lowest loading has been assessed: if it included a theoretical value added, the factor has been retained; if it did not provide a theoretical contribution, the exploratory factor analysis procedure was repeated to generate a valid factor from the alpha point of view.

Once all the factors for the area of analysis have been confirmed and thus accepted, the configuration of the constructs of the theoretical model can be accurately designed. Indeed, through exploratory factor analysis and Cronbach's alpha validation, it has been possible to find an answer to the questions "How many factors do we have?" and "What are the items of each factor?". In order to better interpret the results and to ease the SEM path analysis, the items have been renamed according to the respective factors they were assigned to.

3.8.3 Structural Equation Modelling

SEM is a statistical technique which integrates several multivariate methods into one model fitting framework. For instance, it includes confirmatory factor analysis, linear regression or path analysis.

As affirmed by Bagozzi (2011), SEM is a procedure for testing, measuring and predicting, and thus it allows to examine the relationships between a set of one or more independent variables, either continuous or discrete, and one or more dependent variables, either continuous or discrete. This concept is revisited and detailed by Shah and Goldstein (2006), which affirm that the main goal of SEM is to determine whether a given model is valid or not, rather than seeking a model which perfectly fits with the given dataset.

The term "Structural Equation Modelling" itself already contains and illustrate a basic characteristic: processes are represented through series of structural equations, which can be modelled in order to better visualized the examined processes. In practice, the models consist of observed variables, also called measured, and unobserved variables, also called latent: the former are items which can be measured – e.g. the responses of a survey -, the latter cannot be directly quantified because they are not directly measured.

This set of techniques perfectly matches with the requirements of this research, which aims at testing and validating a theoretical model. In particular, path analysis is the specific tool implemented, because it allows to carry out statistical analysis over models, thus testing structural relationships among measured and latent variables (Shah and Goldstein, 2006). Models are commonly converted in visual forms with path diagrams, which are described by Kaplan (2008) as a graphical representation of the relationships existing between a set of variables.

Going into detail, diagrams consists of two parts: measurement model and structural model. On one hand, the measurement model aims at examining how the constructs are related to observed variables, and so it defines the latent ones; on the other hand, the structural model aims at analysing the causal relationships between latent variables.

In practice, the analysis has been developed as detailed in Figure 9.

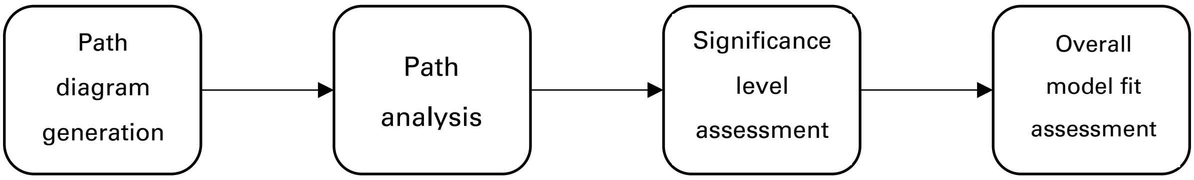

Figure 9: Steps of the SEM analysis

Path diagram

The process of factor analysis and the validation with the Cronbach's alpha allowed to understand the proper design of the model, in terms of number of factors and items' allocation to them.

Afterwards, the constructs have been generated and represented by means of latent variables, associating the items between them according to the information coming from the factorization process.

Concerning the control variables, they have been represented as simple measured variables. In this sense, it is also important to remind that, as far as the categorical variables are concerned, just eight countries have been included into the path diagram to represent the country, leaving the ninth as the baseline. This means that the observations and the final discussions are drawn as a comparison with the level of innovation of the reference country.

The graphical representation of the theoretical model has been performed in Stata through the SEM builder function. In detail, a model can be constituted by rectangles, which represent measured variables – i.e. items or control variables -, ovals, which represent latent variables, and arrows, which represent the paths. Figure 10 illustrates an example of possible path diagram.

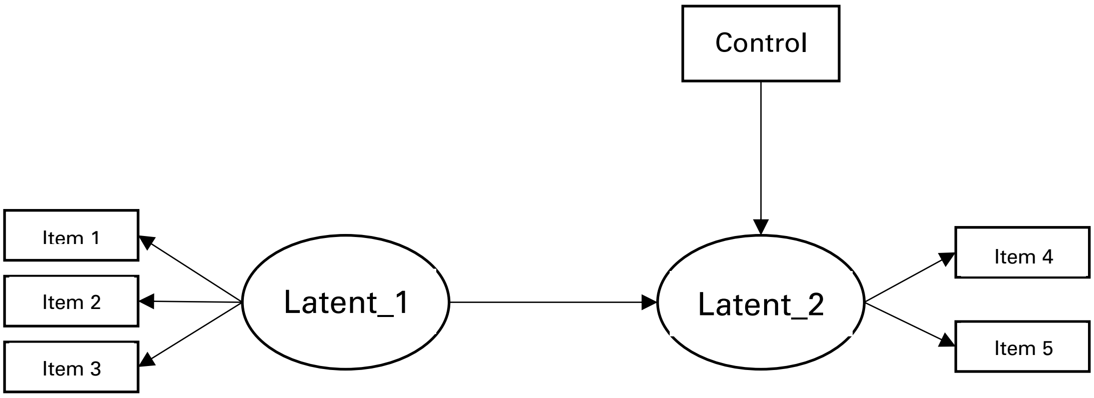

Figure 10: Example of a SEM path diagram's graphical representation

Path analysis

This step can be implemented through different methods; this study has opted for the maximum likelihood technique.

This method can be run in two different version: including or excluding missing values.

The former alternative lead to a higher size of the sample, since it considers all the available observations by predicting all the empty values; the latter results in a lower sample size – due to listwise omission of the observations with missing values. However, if the values are not missing at random, the former is the more reliable option.

Given the high number and non-random pattern of missing values, the maximum likelihood has been run considering the option "without missing values". As a consequence, the number of observations available to test the model significantly decreased.

This issue is addressed more in detail in the sub-section related to the limitations.

Afterwards, the results of the estimation have been evaluated, considering two perspectives: significance of the relationships within the diagram – i.e. arrows – and goodness of fit of the overall model.

Assessment of the significance level

In statistical hypothesis testing, the significance is strictly related to the concept of p-value (p), a parameter defined as the level of marginal significance within a statistical hypothesis test. More precisely, a parameter (α) is defined to identify the probability of rejecting the null hypothesis, given that it was true; the p-value of a result is the probability of obtaining a result at least as extreme, given that the null hypothesis was true. The result is statistically significant if and only if $p < \alpha$.

Generally, the significance level thresholds for a study are chosen a-priori, during the data collection phase, and typically they are arranged as depicted in Table 11.

SCORE	LEVEL OF SIGNIFICANCE	REPRESENTATION
$p \geq 0.100$	Not acceptable	
$0.050 \leq p < 0.100$	Acceptable	*
$0.010 \leq p < 0.050$	Good	**
$p < 0.010$	Optimal	***

Table 11: Thresholds of the p-value

It is possible to conclude that, the stricter the referential threshold, the more reliable is the result and, if the p-value is higher than 10%, the result cannot be considered statistically significative.

Assessment of the overall model fit

Moving to the goodness of the overall model, researchers suggest a broad variety of indices which can be considered. Furthermore, it is important to remark the existing trade-off between the model fit and its simplicity; indeed, a saturated model – where all the possible paths between the variables are considered – has always a perfect fit, but the complexity rises and the model loses of meaning.

In practice, this thesis focuses the attention on the absolute indicators, and not the comparative ones, since they do not require a baseline comparison and thus they are easier to be interpreted.

The first considered index is CD, which is used as a guideline to measure the accuracy of the model. CD is sometimes referred to as the R^2 squared of the overall model as it explains how well observed outcomes are replicated by the model, based on the proportion of total variation of outcomes it explains.

$$CD = \frac{MSS}{TSS} = \frac{(TSS - RSS)}{TSS}$$

where MSS (model sum of squares) is the sum of the squares of the prediction from the linear regression minus the mean for that variable; TSS (total sum of squares) is the sum of the squares of the measurements minus their mean; RSS (residual sum of squares) is the sum of the squares of the measurements minus the prediction from the linear regression.

As underlined by Moore, Notz and Fligner (2013), the score of this index can lead to four different level of goodness, as illustrated in Table 12.

THRESHOLD VALUE	GOODNESS OF THE OVERALL MODEL
$CD \geq 0.700$	Optimal
$0.500 \leq CD < 0.700$	Good
$0.300 \leq CD < 0.500$	Acceptable
$CD < 0.300$	Not acceptable

Table 12: Thresholds of the CD

Afterwards, RMSEA has been computed. This parameter is currently the most popular measure of model fit and it is reported in most of the studies that use SEM (Browne and Cudeck, 1993; Hu and Bentler, 1999). This index, as its formula clearly shows, is positively biased – i.e. tends to be too large – by the sample size and by the degree of freedom:

$$RMSEA = MAX\left(\sqrt{\frac{(\chi^2 - df)}{[df * (N-1)]}};\ 0\right)$$

where N is the sample size, df the degrees of freedom of the model and χ^2 the result of the chi-square test.

Concerning the thresholds, as stated by Fabrigar, Wegener, MacCallum and Strahan (1999), the classes can be defined according to Table 13.

THRESHOLD VALUE	GOODNESS OF THE OVERALL MODEL
RMSEA < 0.050	Optimal
0.050 ≤ RMSEA < 0.080	Good
0.080 ≤ RMSEA < 0.100	Acceptable
RMSEA ≥ 0.100	Not acceptable

Table 13: Thresholds of the RMSEA

Finally, the SRMR has been measured. This index is defined as the standardized difference between the observed correlation and the predicted correlation.

It is a positively biased measure and, as stated by Baron and Kenny (1986), this bias is greater for small sample sizes studies.

The classification of fit level stemming from this index is the same as for the RMSEA, as underlined by Hu and Bentler (1999). Anyway, for the sake of completeness, the thresholds are reported in Table 14.

THRESHOLD VALUE	GOODNESS OF THE OVERALL MODEL
SRMR < 0.050	Optimal
0.050 ≤ SRMR < 0.080	Good
0.080 ≤ SRMR < 0.100	Acceptable
SRMR ≥ 0.100	Not acceptable

Table 14: Thresholds of the SRMR

To conclude, in case the overall model fit is not adequate, it must be examined the possibility to realize some slight modification to enhance the values assumed by the indices.

In this sense, the extant literature suggests introducing the covariances between error terms into the model, when the interaction is justified by the theory; correlating within-factor error is easier to justify than across latent variables correlations, however it is essential that the statistical and substantive impacts are clearly discussed (Hooper, Coughlan and Mullen, 2008). Additionally, the overall fit can be improved also by excluding a variable from the model or by inserting a new one. However, as suggested and demonstrated by Spirtes, Scheines and Glymour (1990), the modifications rarely improve the fit of a model.

3.9 Ambidexterity

As explained in the previous sub-sections, the constructs of the proposed model have been generated as latent variables, exploiting the information stemming from the first steps of the data analysis phase – i.e. exploratory factor analysis and Cronbach's alpha. However, as anticipated at the end of section 3.5, the operationalization of ambidexterity followed a completely different procedure.

Indeed, ambidexterity has been computed as interaction between other two latent variables – i.e. exploitation and exploration. To estimate it, the model has been firstly fitted without the interaction term; afterwards, by using linear regression predictions, the factor scores for the exploitation and exploration constructs have been computed and later mean-centred to reduce the potential multi-collinearity. Finally, ambidexterity has been generated according to a new method.

Going into detail, as deeply illustrated in the literature review, the interaction between exploit and explore has been computed in the past according to different perspectives, without finding a general consensus and thus a formulation. In order to overcome this issue and solve the conflict, this thesis wants to propose an alternative way to operationalize it, which simultaneously considers the combined and balance dimensions.

In practice, the following formula has been implemented:

$$Ambidexterity = \frac{(Exploitation^{+} + Exploration^{+})}{|Exploitation - Exploration| + 1}$$

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; on the other hand, the denominator includes the absolute difference between exploitation and exploration, which is perfectly in line with the balance dimension theory. Therefore, this method is complete from a theoretical point of view, as the main drawbacks related to sum or multiplication – i.e. difficulties in detecting the level of balance between the two strategies – and related to absolute difference – i.e. enterprises scoring low in both approaches considered ambidextrous – are overcome.

Moving on to the practice, two adaptions have been applied to refine the formula.
First of all, it is important to underline that Stata automatically performs a standardization, creating a new a variable with mean 0 and standard deviation 1; as a consequence, exploitation and exploration can assume values below 0. Therefore, the scores have been rescaled so that the ambidexterity had positive scores.
Additionally, another issue was represented by the possibility of having a value of zero at the denominator. A constant value has been added to the absolute difference between exploit and explore to prevent this potential threat; the parameter has been assigned a value of 1 since, in case exploitation and exploration's scores were equal, by setting at 1 the denominator, the level of ambidexterity would just depend on the numerator – i.e. the combined dimension.

This new approach to operationalize ambidexterity also wants to avoid the possibility of suffering from multicollinearity, the main drawback of the multiplication method. Indeed, in a linear regression model, predictors should not be linearly correlated. If a significant linear correlation exists between two or more regressors, the model is said to be affected by multicollinearity. Multicollinearity can lead to inaccurate estimation of the regression coefficients. In a situation of multicollinearity, it may even occur that the CD is close to 1, while the regression coefficients of the predictors are not significantly different from 0.
In order to check the level of multicollinearity, the pair-wise correlation between the observed variables has been inspected. The correlation tables are presented in sub-section 4.1.3.

4. RESULTS

This chapter has the purpose of illustrating the outcomes of the analyses carried out according to the statistical techniques described in the methodology discussion.

In practice, this stage is divided into two main sections: (i) the internal consistency of the measurement model is shown through the results of the exploratory factor analysis and Cronbach's alpha tests and (ii) the structural model is evaluated by exhibiting the significance level of all the relationships which constitute it and the overall indices of fit.

4.1 Measurement Model

The measurement model, as stated in sub-section 3.8.3, aims at examining how the constructs are related to items. In practice, the model has been accurately designed through the exploratory factor analysis and, afterwards, its quality has been assessed with the Cronbach's alpha. These two statistical techniques have been applied over the final dataset generated in the data preparation step of the methodology. Finally, the validity of the new formula to operationalize ambidexterity has been verified by illustrating its lack of multicollinearity.

The three following sub-sections accurately illustrate the outcomes of these statistical testing methods and the respective insights.

4.1.1 Identification of the Constructs

The factor analysis has been performed to summarize the cleaned database, coming from the data preparation phase, into new constructs that are linear combinations of the considered input variables.

The determination of the correct number of factors, as the methodology explained, is the first step to be developed. In order to do that, the functions "factor" of the software Stata has been implemented over the remaining 20 variables and 140 observations. Table 15 exhibits only the factors with positive eigenvalue; for the complete outcome of the factorization process, see Appendix A.

FACTOR	EIGENVALUE	PROPORTION OF VARIANCE EXPLAINED [%]	CUMULATIVE VARIANCE EXPLAINED [%]
Factor 1	6.49039	0.5007	0.5007
Factor 2	2.35476	0.1817	0.6824
Factor 3	1.66772	0.1287	0.8110
Factor 4	1.17010	0.0903	0.9013
Factor 5	0.68294	0.0527	0.9540
Factor 6	0.59571	0.0460	0.9999
Factor 7	0.39112	0.0302	1.0301
Factor 8	0.25143	0.0194	1.0495
Factor 9	0.18450	0.0142	1.0637
Factor 10	0.12680	0.0098	1.0735
Factor 11	0.04506	0.0035	1.0770
Factor 12	0.00029	0.0000	1.0770

Table 15: Results of the "factor" function

Afterwards, the function "screeplot" has been carried out, producing the elbow-shape of Figure 11.

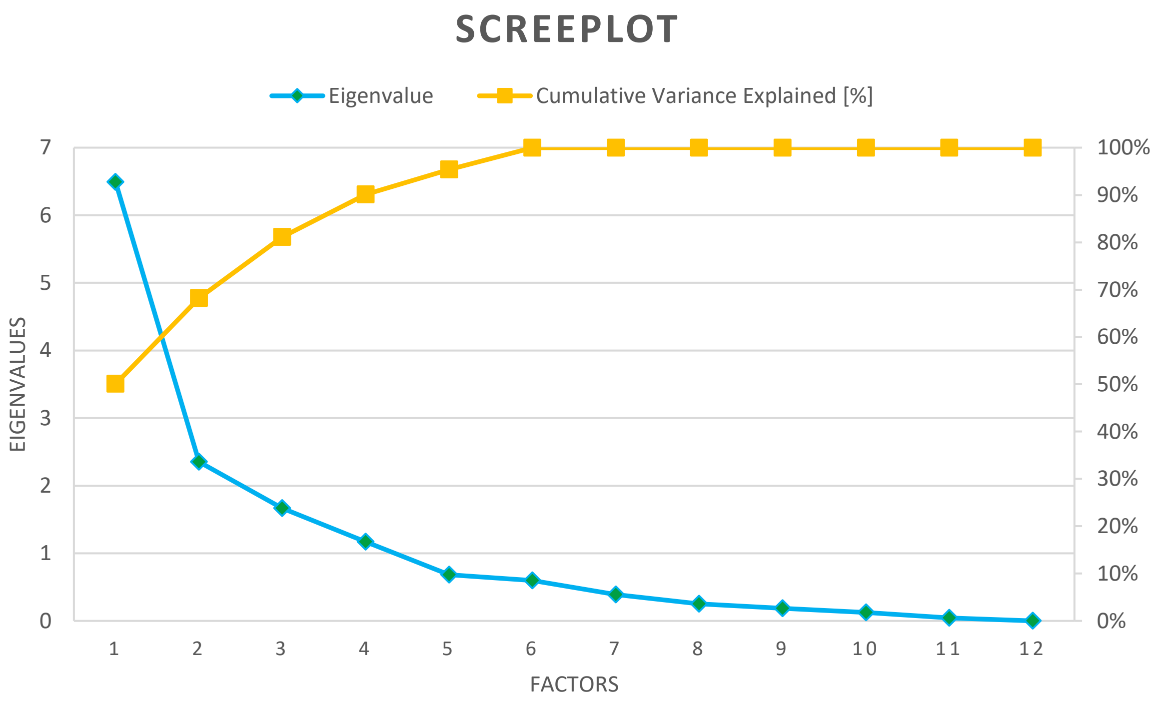

Figure 11: Graphical representation of the results of the "screeplot" function

The measures which must be assessed are two: the eigenvalue and the cumulative variance explained.

Concerning the former, the second column of Table 15 illustrates the eigenvalues of each factor and suggests that the correct number to be generated and retained should be four, since the fifth value is already lower than the threshold – i.e. 1. However, the eigenvalue is not sufficient to carry out a precise and reliable analysis. The second indicator – i.e. the amount of variance explained – is represented by the last column of Table 15. In order to better interpret these values, the scree plot displayed in Figure 11 must be examined. As Dmitrienko, Chuang-Stein and D'Agostino (2007) argue, according to the scree-test, the "elbow" of the graph where the eigenvalues seem to level off is found, and factors or components to the left of this point should be retained as significant. Thus, the plot demonstrate that the correct number of factors should be five. This result is consistent with the underlying concept of the theoretical model proposed in this thesis, which should be made up by five constructs – i.e. BP, SMT, Exploitation, Exploration and IP.

Once determined the proper number, the allocation of each variable to the correct factor started. This step was performed through the “rotate, promax” function which directly showed the best allocation for each of the 20 considered variables. The values have been sorted through the “sortl” function of Stata, in order to make them more readable.

VARIABLE	FACTOR 1	FACTOR 2	FACTOR 3	FACTOR 4	FACTOR 5	UNIQUENESS
EXPLT_1	**0.9634**	-0.1026	-0.0158	-0.0251	-0.0013	0.1707
EXPLT_2	**0.8551**	0.0583	-0.0576	-0.0610	0.1414	0.2475
EXPLT_3	**0.5593**	0.0744	0.0977	0.1352	-0.1168	0.5104
EXPLT_4	**0.4784**	0.0355	0.2233	0.1410	0.0766	0.4332
EXPLR_1	-0.0276	**0.8474**	0.0496	0.0476	0.0205	0.2251
EXPLR_2	0.0256	**0.7887**	-0.0218	0.0999	-0.0095	0.3283
EXPLR_3	-0.1714	**0.7799**	-0.0247	0.0733	0.1147	0.4176
EXPLR_4	0.1120	**0.7293**	0.1170	-0.1007	-0.1848	0.3561
IP_1	0.0069	-0.0038	**0.7082**	0.1192	-0.0295	0.4411
IP_2	0.0309	0.0646	**0.6372**	0.0738	0.0365	0.4677
IP_3	0.0721	0.3490	**0.5284**	-0.1590	0.1148	0.3642
IP_4	-0.0493	0.1413	**0.4492**	-0.2007	0.0035	0.7647
SMT_1	-0.1089	-0.1011	0.0472	**0.7084**	0.2232	0.4523
SMT_2	0.0664	0.3049	-0.1574	**0.6282**	-0.0999	0.4714
SMT_3	0.0509	-0.1862	0.1552	**0.6258**	-0.1580	0.5798
SMT_4	0.0769	0.2002	-0.0812	**0.6134**	0.1134	0.4472
SMT_5	-0.0443	-0.0165	0.3516	**0.5195**	-0.0204	0.5466
BP_1	-0.0299	-0.0080	0.0335	0.0698	**0.9252**	0.1058
BP_2	0.0201	0.0072	0.0893	-0.0744	**0.8993**	0.1548
BP_3	0.1064	-0.0235	-0.0810	0.0618	**0.8966**	0.1494

Table 16: Results of the “rotate, promax” function

By looking at Table 16, each variable can be easily associated to the respective factor, according to the loading indicator and following the procedures presented in sub-section 3.8.1.

4.1.2 Validation

This sub-section aims at separately assessing the validity of each of the five constructs that forms the theoretical model. In practice, the items' allocation and the factors' alpha are checked to prove the statistical validity of the measurement model.

Factor 1: Exploitation

All the scores associated with the construct exploitation are illustrated in Table 17.

ITEM	QUESTION OF THE SURVEY	LOADING	UNIQUENESS
EXPLT_1	In our production function, we systematically invest in incrementally improved equipment, tools and techniques to improve the performance of our production processes	0.9634	0.1707
EXPLT_2	In our production function, we systematically acquire state-of-the-art knowledge, skills, equipment, tools and techniques	0.8551	0.2475
EXPLT_3	In our production function, we systematically acquire new managerial and organizational skills that are important for production	0.5593	0.5104
EXPLT_4	In our production function, we systematically strengthen and upgrade current knowledge and skills for familiar production processes and technologies	0.4784	0.4332

Table 17: Results of the validation process for the exploitation construct

The eigenvalue – i.e. 6.49 – and the outcome of the alpha test – i.e. 0.83 – clearly demonstrate that the construct is internally consistent. Moreover, each single item possesses an acceptable loading and a uniqueness score below the threshold of 0.6. Hence, no issues should emerge in the subsequent phases of the statistical analyses – i.e. the SEM technique.

Factor 2: Exploration

All the scores associated with the construct exploration are illustrated in Table 18.

ITEM	QUESTION OF THE SURVEY	LOADING	UNIQUENESS
EXPLR_1	In our innovation function, we systematically support and encourage creativity, inventiveness and participation in product innovation and improvement	0.8474	0.2251
EXPLR_2	In our innovation function, we systematically invite and use feedback and ideas from external partners (customers, suppliers, research institutes) to improve our product development practices and performance	0.7887	0.3283
EXPLR_3	In our innovation function, we systematically adapt to changes in the competitive environment by innovating and improving our products	0.7799	0.4176
EXPLR_4	In our innovation function, we systematically use clear project targets, project phase standards and project management regulations for our product development activities	0.7293	0.3561

Table 18: Results of the validation process for the exploration construct

The eigenvalue is set at 2.35 and thus it is largely above the threshold of 1, and the score of Cronbach's alpha is slightly higher than the minimum acceptability level – i.e. 0.76. Therefore, the construct can be considered internally consistent. Moving on to the single items, all the loadings are extremely high and the uniqueness score below 0.6, meaning that all the four items almost equally contributes in explaining the factor explore.

Factor 3: Innovation Performance

All the scores associated with the construct IP are illustrated in Table 19.

ITEM	QUESTION OF THE SURVEY	LOADING	UNIQUENESS
IP_1	*Over the past three years, our performance in total new product development costs as a percentage of sales, compared to the competitors' one, on average was …*	0.7082	0.4411
IP_2	*Over the past three years, our performance in employee performance on health and safety, quality of life, motivation and satisfaction, knowledge and* skills*, compared to the competitors' one, on average was …*	0.6372	0.4677
IP_3	*Over the past three years, our performance in project planning accuracy (e.g. percentage of projects over-running planned project lead time, time-to-market or budget), compared to the competitors' one, on average was …*	0.5284	0.3642
IP_4	*Over the past three years, our performance in launch of "smart" (digitalized, intelligent) products (with in-built sensors, microprocessors, memory) (Internet of Things and Services), compared to the competitors' one, on average was …*	0.4492	0.7647

Table 19: Results of the validation process for the IP construct

This construct is the one which cause the most significant issues.

First of all, even if the eigenvalue is more than acceptable – i.e. 1.67-, alpha is 0.67, thus slightly lower than the threshold of 0.7. This is probably related to the remarkable number of missing values associated to IP, since the majority of empty values were related to this section of the survey. Hence, this limitation could have affected the outcome of the alpha test. In particular, variable IP_4 could be the main source of troubles, since it also has a uniqueness score higher than 0.6. Nevertheless, this cannot be considered a remarkable issue, because the factor loading of this item is acceptable and its theoretical meaning is perfectly in line with the requirements of this thesis, since it is strictly related to the concept of IoT, one of the key technologies of I4.0.

Factor 4: Smart Manufacturing Technologies

All the scores associated with the construct SMT are illustrated in Table 20.

ITEM	QUESTION OF THE SURVEY	LOADING	UNIQUENESS
SMT_1	In our company, the degree of use of computer-aided process planning (CAPP) is…	0.7084	0.4523
SMT_2	In our company, the degree of use of manufacturing resource planning (MRP II) / enterprise resource planning (ERP) is…	0.6282	0.4714
SMT_3	In our company, the degree of use of automatic identification / Bar code systems / RFId is…	0.6258	0.5798
SMT_4	In our company, the degree of use of "Smart" ICT applications supporting supplier/customer collaboration, connectivity (plants, equipment, robots, lines, workers), data processing (big data) / information mining, modelling/simulation is…	0.6134	0.4472
SMT_5	In our company, the degree of use of advanced manufacturing technologies (e.g. water and photonics-based / Laser cutting, additive manufacturing / 3D printing, high precision technologies, micro/nano-processing) is…	0.5195	0.5466

Table 20: Results of the validation process for the SMT construct

The results related to the factor are all acceptable in this case, since both the eigenvalues and the alpha are above the respective threshold – i.e. 1.17 and 0.71 respectively. Additionally, also the values associated to each single item are tolerable, since the loadings are all sensibly over the lower bound and the values of uniqueness indicate that all the five items provide additional value in defining the construct.

Factor 5: Business Performance

All the scores associated with the construct BP are illustrated in Table 21.

ITEM	QUESTION OF THE SURVEY	LOADING	UNIQUENESS
BP_1	Our average net profit compared to our main competitors over the past three years was…	0.9252	0.1058
BP_2	Our average return on sales compared to our main competitors over the past three years was…	0.8993	0.1548
BP_3	Our average profit growth compared to our main competitors over the past three years was…	0.8966	0.1494

Table 21: Results of the validation process for the BP construct

Even if the eigenvalue is relatively low – i.e. 0.68 -, this factor has been maintained. The reason behind this choice, has already explained in sub-section 4.1.1, lies in the elbow-shape of the scree plot and in the cumulative variance explained by the five retained factors. Beyond that, the value of alpha is particularly high – i.e. 0.93 -, proving how these three items are correlated and thus the construct internally coherent. Looking at the three items separately, all of them present a significantly high value of loading, showing again how this construct is consistent, and a uniqueness score largely acceptable.

In sum, the processes of exploratory factor analysis and validation through Cronbach's alpha has demonstrated the validity of the measurement model, as all the constructs are internally consistent and the items correctly allocated.

4.1.3 Ambidexterity

As the methodology underlined, structural ambidexterity has been operationalized following a new procedure. In practice, it has been represented by means of a measured variable instead of a latent one, by implementing the following formula.

$$Ambidexterity = \frac{(Exploitation^{+} + Exploration^{+})}{|Exploitation - Exploration| + 1}$$

The main advantage of this new method to calculate the structural ambidexterity lies in the possibility to overcome the multicollinearity issue.

MULTIPLICATION	*Ambidexterity*	*Exploitation*	*Exploration*
Ambidexterity	1	-	-
Exploitation	**0.7763**	1	-
Exploration	**0.7708**	0.2137	1

Table 22: Multicollinearity level between the three variables, when ambidexterity is computed as multiplication between exploitation and exploration

NEW FORMULA	*Ambidexterity*	*Exploitation*	*Exploration*
Ambidexterity	1	-	-
Exploitation	**0.3521**	1	-
Exploration	**0.3435**	0.2137	1

Table 23: Multicollinearity level between the three variables, when ambidexterity is computed with the new proposed formula

Table 22 and Table 23 illustrate the correlation between the latent variables – i.e. exploitation and exploration – and ambidexterity. It can be easily noticed that the performance is remarkably better in the second case, since ambidexterity is less correlated with the other two variables. This means that the new approach to operationalize ambidexterity should help in avoiding the possibility of suffering from multicollinearity; indeed, in a linear regression model, predictive variables should not be linearly correlated. As a consequence, having prevented this critical issue, the SEM implementation is eased.

4.2 Structural Model

Subsequently to the measurement model, SEM has been adopted in order to test the validity of the hypotheses proposed and verify the possible influence of unobserved variables – i.e. the control variables. Thus, this section aims at assessing the structural model – defined in the methodology as the set of causal relationships between latent variables – in order to identify the significant paths.

In practice, once generated the diagram through the builder tool, the model has been run over the dataset made up by 140 observations and 20 variables. As the methodology already explained, the statistical technique implemented is the maximum likelihood without including missing values. As a result, the number of available observations drop to 62. The outcomes have been assessed through the p-value indicator, a parameter which reflects the level of significance of a causal relationship between variables of a path diagram.

Considering the intervals of p-value illustrated in Table 11, the maximum likelihood analysis produced the results exhibited in Figure 12 and Table 24. [5]

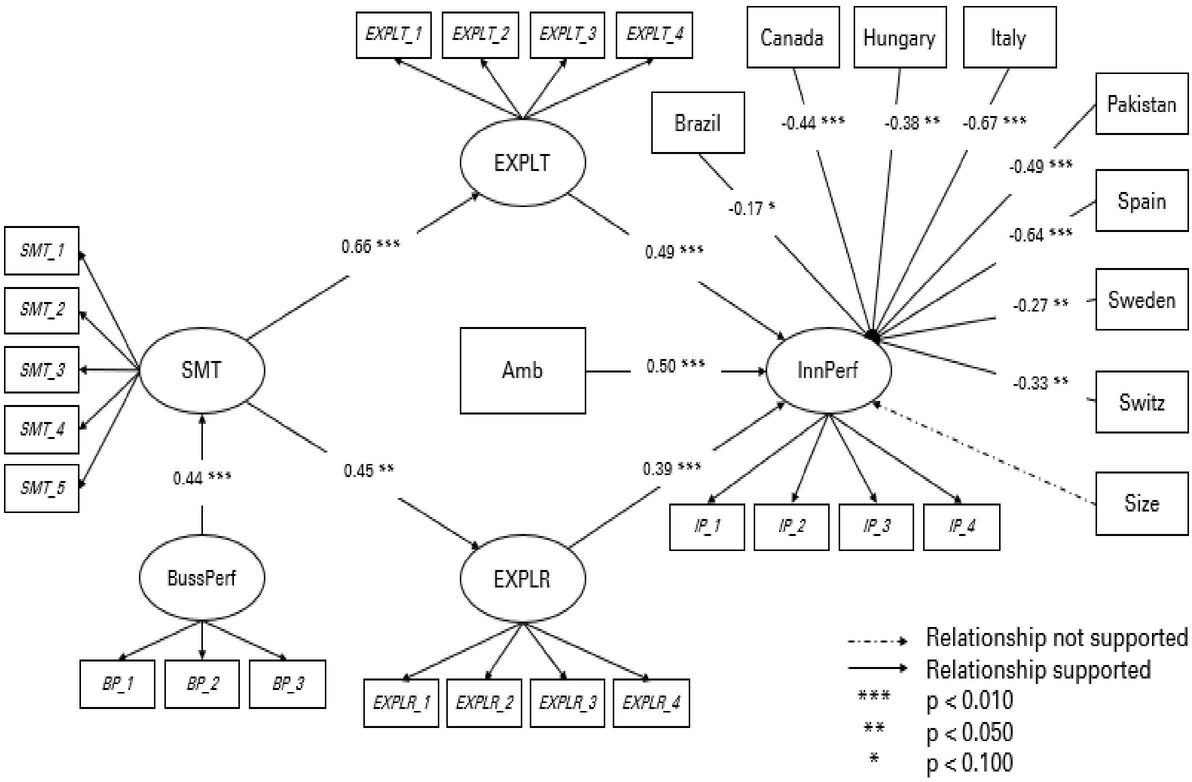

Figure 12: Results of the SEM path analysis

HYPOTHESIS	STD PATH COEFFICIENT	P VALUE	STATISTICAL VALIDITY	RELIABILITY
BP → SMT	0.44	0.005	Supported	Strong
SMT → Exploitation	0.66	0.001	Supported	Strong
SMT → Exploration	0.45	0.010	Supported	Medium
Exploitation → IP	0.49	0.000	Supported	Strong
Exploration → IP	0.39	0.001	Supported	Strong
Ambidexterity → IP	0.50	0.000	Supported	Strong

Table 24: Results of the hypotheses testing analysis

[5] The SEM analysis calculates also the significance level of the relationship between a latent and all its measured variables; however, since the measurement model has already been examined in the previous section, only the outcomes related to the structural model are presented here.

Clearly, the SEM analysis supports and demonstrates the validity of all the six hypotheses examined. In detail, the p-values assure an optimal significance level for almost all the path between the latent variables. Therefore, the research questions of this thesis can be answered through the proposed model.

The discussion of the results is deeply addressed in section 5.1.

Moving on to the control variables, Denmark has been arbitrary selected as reference country for the analysis. The SEM produced the outcomes of Table 25.

HYPOTHESIS	STD PATH COEFFICIENT	P VALUE	STATISTICAL VALIDITY	RELIABILITY
Company Size → IP	0.014	0.893	Not supported	-
Brazil → IP	- 0.17	0.074	Supported	Weak
Canada → IP	- 0.44	0.000	Supported	Strong
Hungary → IP	- 0.38	0.010	Supported	Medium
Italy → IP	- 0.67	0.000	Supported	Strong
Pakistan → IP	- 0.49	0.009	Supported	Strong
Spain → IP	- 0.64	0.001	Supported	Strong
Sweden → IP	- 0.27	0.018	Supported	Medium
Switzerland →IP	- 0.33	0.019	Supported	Medium

Table 25: Results of the control variables testing analysis

Concerning the company size, the SEM does not demonstrate the existence of a significant influence over the IP of a firm, given the extremely high p-value of the relationship.

On the other hand, country produces interesting and remarkable outcomes, as all the eight countries directly impact over the IP. In detail, all of them possess a negative path coefficient, meaning that the reference dummy variable – i.e. Denmark – probably has outstanding IP, according to the responses of the survey.

More detailed discussions are presented in section 5.2.

4.3 Overall Model Fit

Once shown the outcome of the path analysis, it is important to display also the performance of the overall model in terms of goodness of fit. As clarified in the methodology, this thesis relies on three indices – i.e. CD, RMSEA and SRMR.

INDEX	PERFORMANCE	GOODNESS LEVEL
CD	0.992	Optimal
RMSEA	0.095	Acceptable
SRMR	0.119	Not acceptable

Table 26: Thresholds of the models

Considering the thresholds illustrated in Table 26, the model proves to be acceptable for two indices out of three.

In detail, the score of CD is outstanding, since it is near the perfection – i.e. 1 -, whereas RMSEA is slightly acceptable, being below the rejection threshold. Anyway, SRMR is not completely acceptable, since it exceeds the upper bound, set at 1. The reason behind that is probably the low number of observations available to test the model, since both RMSEA and SRMR depend on this parameter, which represent the main limitation of the conducted work, as it is deeply underlined in sub-section 6.2.1.

5. DISCUSSION

Once illustrated the statistical results of the model, their main interpretation from a theoretical viewpoint is presented here.
In detail, the chapter discusses: (i) the hypotheses; (ii) the control variables and (iii) the overall model.

5.1 Hypotheses

By looking at the p-values, it can be concluded that all hypotheses are supported, meaning that all the assumed relationships have been statistically verified. At this point, it is important to analyse each single hypothesis by examining the path's coefficient in order to draw meaningful insights.

H1: Business Performance → Smart Manufacturing Technologies

Path coefficient: 0.44 | P-value: 0.005 | Statistical validity: supported

The theoretical model, by supporting this hypothesis, gives evidence that firms which outperform competitors, from a financial viewpoint, are in a favourable position to adopt SMTs within the organization.

The underpinning principle of this theory is that SMTs' implementation is a challenging step for companies, since it can be very costly (Lin and Chen, 2012) and forces them to undertake some relevant changes – e.g. establishing dedicated units to effectively analyse big data. Hence, enterprises with outstanding BP can undertake complex changes, since the slack resources they possess help in facing such costly investment and protect in case of failure – i.e. depletion of resources.
Indeed, according to BP construct's items – i.e. net profit, profit growth and return on sales -, it is easy to associate good BP with higher financial availability which can be deployed; this means that such organizations possess resource to carry out investments in I4.0.
As explained in the literature gaps section, no studies have analysed this relationship before; as a consequence, it is provided for the first time an empirical evidence of the enabling role of BP over SMTs.

Additionally, the empirical evidences coming from this hypothesis allow to assess in a critical way two STM's barriers presented by O'Donovan et al. (2015).

- *Historical investment in ICTs and automation*: organization may be unwilling to substitute old machinery which has received a significant investment in the past;
- *High risk and disruption*: the possibility of achieving results different from the expectations is always existing, thus the desire to undertake a I4.0 project may remain weak, if it is not strictly necessary to survive in the market.

Concerning the first obstacle, the conducted analyses has demonstrated that unwillingness can be overcame if companies have the resources necessary to finance the investments; moving to the second one, it has been certified that enterprises can be prone to invest not because they need to survive, but because financial availability protect them from disruption risk.

Finally, this work confirms the theory that higher investments, not only in I4.0, are triggered by positive financial indicators, which has been previously investigated just by few studies.

H2: Smart Manufacturing Technologies → Exploitation

Path coefficient: 0.66 | P-value: 0.001 | Statistical validity: supported

The theoretical model, by supporting this hypothesis, gives evidence of the positive and significant influence of SMTs' adoption level over operations' exploitation.

Introduction of SMTs facilitate companies' exploitation of their operations, since the ultimate goal of such technologies is easing the automatization of some production phases. Indeed, the generation of smart factories will decrease the wastes and enhance the productivity of the firms, leading to a higher level of exploitation.

This hypothesis provides empirical support to the study by Gastaldi et al. (2018), who argue that enterprises which undertake a digital transformation have the objective of optimally exploiting the resources and achieving efficiency in terms of time savings, cost reduction or managerial simplification.
Additionally, the conducted study not only confirms the already existing hypothesis of ICT's positive impact over exploitation, but it also provides, for the first time, empirical support for the enabling role of SMTs over exploitation in the production field. As a consequence, enterprises able to introduce I4.0 are in a favourable position to satisfy actual environmental condition, by adapting the existing competencies to the needs of existing customers (Harry and Schroeder, 2000). Therefore, it is possible to affirms that SMTs do not only provide the already demonstrated operational benefits – i.e. reducing resource utilization and increased energy savings (Ali and Azad, 2013) -, but they also allows companies to bring improvements in

existing product, remaining on the same technological trajectory (Benner and Tushman, 2002). These benefits are strictly related to the OTs – i.e. additive manufacturing, computer-aided process planning – included into the construct SMTs. Obviously, also the other ICTs included in the construct – i.e. smart ICTs applications, RFId and ERP – bring benefits related to operations' exploitation. This is consistent with the research of Revilla et al. (2007), who consider the convergent ICTs dimension – i.e. technologies used to connect people, thus facilitating coordination and communication of tacit knowledge – as exploitation antecedent.

Therefore, with statistical evidence, it can be concluded that SMTs involve two different benefits: first of all, the one strictly associated to their implementation; then, the possibility to enhance companies' ability to exploit their operations thanks to ICTs and OTs.

H3: Smart Manufacturing Technologies → Exploration

Path coefficient: 0.45 | P-value: 0.010 | Statistical validity: supported

The theoretical model, by supporting this hypothesis, gives evidence of the positive and significant influence of SMTs' adoption level over innovations' exploration.

This result proves a relationship less intuitive than the previous one. In detail, by introducing SMTs, enterprises can revolutionize the data collection process, thanks to smart objects which are able to gather an enormous amount of information and thus support the manufacturing activities. As a consequence, firms can generate smart factories and extract valuable information to enhance their exploration strategies.
In the past, scholars have already investigated the relationship between ICTs and SMTs (e.g. Lee et al., 2008; Xue et al., 2012), arguing that ICTs are a good antecedent since they support data collection. This work agrees with this stream of researches, and empirically validates the enabling role of I4.0 for exploration strategies. Indeed, thanks to BD&IA, companies can more easily increase variation and experimentation and thus attain novelty in product innovation. For the first time, it is empirically supported that enterprises which implement SMTs – e.g. computer-aided process planning, RFId, smart ICTs applications, ERP, etc. – can increase their exploration capabilities and then extract the information related to environmental trends. This is especially possible when data are used to perform predictive and prescriptive analyses, which allow to anticipate the future and thus explore new opportunities and experiment new ideas. The organizations have the desire of exploring new ways of extracting value from previously digitised data (Gastaldi et al., 2018) and, once learn how to do that, it is validated that the

extrapolated information favours creative learning and innovation – i.e. the exploration essence (Rosenkopf and Nerkar, 2001).

Additionally, it is interesting to simultaneously examine the path coefficients of H2 and H3 to make a comparison.
As the scores clearly exhibit, SMTs have a greater influence over exploitation rather than over exploration. The reasons behind that are:

- The usage of BD&IA, essential requirement for achieving innovation's exploration, forces companies to go through fundamental changes, sometimes also establishing dedicated units for analysing data, which can cause them some difficulties in extracting information from the gathered data. On the other hand, the exploitation of the operations processes is an easier objective, which the introduction of SMTs can make even more immediate;
- As supposed by Gastaldi et al. (2018), a possible path related to digitisation is formed by two steps: the initial objectives of the digitisation are related to exploitation and, consequently, the solutions introduced allow the exploration of new trajectories. The result of the conducted analyses could signify that not all the enterprises included in the sample have reached the second step of the digitisation process.

H4: Exploitation → Innovation Performance

Path coefficient: 0.49 | P-value: 0.000 | Statistical validity: supported

The theoretical model, by supporting this hypothesis, gives evidence of the positive and significant influence of firms' degree of operations' exploitation over their overall IP.

As the review of the literature showed, this relationship has been deeply addressed in the past, without finding a general consensus.
The conducted study determines a positive and linear relationship between exploitation and IP, suggesting that companies become increasingly innovative, even if the exploitation level is very high. As a consequence, this work supports some remarkable publications (e.g. He and Wong, 2004; Lee, Lee and Garrett, 2017), which demonstrate that exploitation has a positive effect on IP, without associating any negative counter-indication related to exceeding in this strategy. However, refusing the theory of Atuahene-Gima and Murray (2007), who find a U-shape relationship between these two aspects, this thesis proves a positive and linear relationship, suggesting that exploitation is positively linked to IP at every magnitude.

Additionally, even the idea of diminished returns as a consequence of high exploitation level and thus organizational inertia is rejected. The explanation could be that exploitation is restricted just to a separated department of the organization – i.e. the production one -, thus bringing lower rigidity, since only a part of the firm is focused on this strategy.

Going more into detail, the confirmation of this hypothesis makes it possible to assert that, if enterprises follow an exploitation strategy for the production processes, they will enjoy direct and positive consequences over their IP, given more suitable processes, productivity improvements and variance reductions. These aspects influence also firm's ability to reach economies of scale and scope, as argue by Auh and Menguc (2005). Therefore, this thesis support Wang and Lam (2019), who point out that, as long as an organization learns, it will positively affect its IP.

This concept is applicable also to the production area alone, where company are in a favourable position to increase the overall IP, if they are able to: strengthen and upgrade current knowledge, invest in incrementally improved equipment, acquire state-of-the-art skills and new managerial skills relevant for production. This is a valuable contribution, since it overcomes the idea that exploitation increases only incremental innovations by focusing the attention on existing product, as it empirically validates the relationship operations' exploitation-IP.

H5: Exploration → Innovation Performance

Path coefficient: 0.39 | P-value: 0.001 | Statistical validity: supported

The theoretical model, by supporting this hypothesis, gives evidence of the positive and significant influence of firms' degree of innovation' exploration over their overall IP.

Even in this case, the review of the extant literature has highlighted a conflict between scholars. He and Wong (2004) demonstrate a positive role of exploration over the overall IP, and Yalcinkaya et al. (2007) prove that exploration has positive effect on both incremental and radical IP separately. Lee, Lee and Garrett (2017) determine that exploration orientation allows enterprises to introduce both radical and incremental product innovation, even if they have hypothesized only a positive influence on radical performance. Katila and Ahuja (2002) find a linear positive relationship but, after having supposed an inverted U-shape, argue that further studies should investigate this relationship, since there is the possibility that only the linear, increasing part of the curve has been detected.

The empirical evidence coming from this thesis validates all these researches, showing that the exploration of new innovative ways to make business improves the IP both in the short and in the long-term – i.e. respectively incremental and radical performance. As a consequence, the initial assumption of negative returns associated with high level of exploration and excessive amount of new knowledge to be handled is refused (Cao et al., 2009).
Going into detail, the results illustrate that companies which pursue exploration strategies within the innovation department benefit from large amount of new knowledge's introduction, since changes can be easily managed. Indeed, exploring within the innovation function allows to embrace breakthrough innovations and, simultaneously, expanding and enriching the organizational knowledge base.

In sum, companies will have the possibility to enhance their IP, if they are able to effectively use clear project targets, support and encourage creativity, use feedback and ideas from external partners and adapt to changes in the competitive environment within the innovation function. Indeed, they will be competitive also in the short-term and they will succeed in diminishing the negative effect associated with development of too much novelty, because exploring within the innovation function allows to reinforce environmental changes' perception and to be effective in the innovation management (Wang and Lam, 2019).

By simultaneously considering the path coefficients of H4 and H5, an interesting comparison can be drawn. First of all, it can be argued that, as companies exploit and explore more, they enhance the new product performance, since their learning processes are improved too (Atuahene-Gima and Murray, 2007).
However, as the scores clearly exhibit, exploitation has a greater influence over IP rather than exploration. This is a quite intuitive result, since benefits coming from exploitation are more immediate and with a greater likelihood. Therefore, it can be concluded that operations' exploitation allows companies to have lower variation in their performance (He and Wong, 2004) and to enjoy benefits in the short-term; on the contrary, innovation's exploration aims at spotting new trend and technological trajectories partially sacrificing productivity (March, 1991), thus obtaining less profitability enhancement since the beginning. Therefore, the proposed model validates and confirms a concept supported by the extant literature.

H6: Ambidexterity → Innovation Performance

Path coefficient: 0.50 | P-value: 0.000 | Statistical validity: supported

The theoretical model, by supporting this hypothesis, gives evidence of the positive and significant influence of firms' degree of ambidexterity, meant as interaction effect between exploitation and exploration strategies, over their overall IP.

The already existing researches have deeply assessed this relationship; however, a few studies have empirically tested such hypothesis. For instance, Katila and Ahuja (2002) and Nerkar (2003) demonstrate that companies able to mix exploitative strategies within the operations and the explorative ones in the innovation function has the capabilities to increase IP. This study certifies the idea that structural ambidexterity can be an effective solution to enhance enterprises IP, rejecting the theory that organizations are unable to be ambidextrous within a single domain (Lavie and Rosenkopf, 2006). Additionally, it is refused also the idea that low returns are associated to the impossibility of managing the conflicting pressures coming from high level of exploitation and exploration (Atuahene-Gima, 2005). Therefore, ambidextrous companies are competitive and innovative both in the short and long-term, overcoming the capability-rigidity paradox by focusing on improving in the existing product-market domains and simultaneously entering in new ones. This outcome also confirms that a significant level of exploitation can improve enterprises' effectiveness in exploring within the innovation function, and a great effort in exploration activities can enhance successful exploitation within the operations' department (Cao et al., 2009).

Structural ambidexterity proves to be a feasible alternative to solve the issue of balancing the divergent nature of exploitation and exploration, by separating them into two different departments (Golden and Ma, 2003), since it recognizes the existence of conflicting mindsets within the organization and makes it effective. Indeed, this configuration enables the simultaneous adoption of exploitative operations strategies, focused on increasing efficiency, and explorative innovation strategies, focused on variation and risk taking. Nevertheless, companies must be careful, because separation must be correctly managed, otherwise it could lead to isolation, with innovation units too far away from the core business.

For the sake of completeness, it is also interesting to simultaneously examine the path coefficients of H4, H5 and H6 in order to make a comparison.

As the scores clearly exhibit, ambidexterity has a greater influence over IP rather than exploitation and exploration. This is a very meaningful result, since it is evidenced that enterprises able to be ambidextrous can reach higher performance.

Anyway, this insight has some limitations: first of all, the path coefficient of H6 is slightly higher than the one of H4, meaning that the impacts on IP are basically the same; secondly, ambidexterity is a measured variable computed as interaction between exploitation and exploration, the other two constructs discussed in this path analysis, and this decreases the reliability of the comparison.

General Considerations

The previous paragraphs illustrate how all the hypotheses of the theoretical model are statistically supported, with five out of six path coefficients higher than 0.4.

Therefore, the conducted work positively solves research question 3, since it can be affirmed that well-performing companies, from a financial perspective, are in a favourable position to achieve brilliant IP. Thus, an answer to Piening and Salge (2015) study has been provided, validating a relationship not clarified by the extant literature, which prevalently investigated the inverse path.

Additionally, by looking at the overall model, it is possible to state that, if enterprises have some constraints and are forced to select just one strategy, they should opt for exploitation. Indeed, once implemented SMTs, exploitation is more easily achievable than exploration – i.e. 0.66 vs 0.45 -, and it impacts more on IP – i.e. 0.49 vs 0.39.

In sum, considering these empirical results, enterprises should adopt new behaviours in order to be innovative: the financial assets should be reinvested in order to introduce SMTs, which allow to become ambidextrous and thus more innovative. In other words, managers should not be satisfied once achieved good BP, and should invest in new breakthrough and useful technologies.

5.2 Control Variables

5.2.1 Company Size

The p-value of the relationship clearly shows that the hypothesis is not supported.

This indicate that the dimension of the firm does not affect the proposed model, and the size does not influence the IP achievable.

This result is in contrast with the extant literature. Ebben and Johnson (2005) prove that small organizations have scarce performance in case they seek to pursue both exploitation and exploration. It has been certified that SMEs face more problems in being ambidextrous, since they can lack of hierarchical administrative systems which can help in managing the contradictory knowledge processes (Lubatkin et al., 2006). Issues related to size could be strictly related also to structural ambidexterity since, accordingly to Voss et al. (2008), this configuration suits large firms but not the small ones, because they cannot easily generate separated BUs.

The reason behind this unexpected result could lie in the fact that larger companies do not have enough flexibility to be ambidextrous (Jansen et al., 2009), and size could represent an obstacle for them as, in many cases, it slows down the process of decision-making, especially when the organization opt for a decentralized structure.
Another explanation could be the way company size has been operationalized since, as explained in the methodology, this computation relies on a strong assumption.
Given the conflicting nature of this relationship and the obtained results, further investigations should be performed.

5.2.2 Country

As already explained, the results are weighted on Denmark – i.e. the arbitrary reference country. The p-values and the path coefficients of the SEM analysis clearly illustrate how all the included countries have a significant and negative impact over IP. This means that companies operating in Denmark enjoy a positive influence, due to environmental conditions, and can achieve outstanding IP more easily than the other analysed country.

Going into detail, Denmark has good environmental condition since, as World Economic Forum Report (2019) shows, it is the best country for macro-economic stability worldwide and it achieves good results also in terms of business dynamism. This is an intuitive outcome, since enterprises operating in less favourable conditions – i.e. Brazilian, Canadian, Hungarian, Italian, Spanish and Pakistani companies – are expected to face more difficulties in reaching good IP. However, the dataset comprehends also firms operating in Sweden and Switzerland, two countries which possess a manufacturing innovation index higher than the Denmark's one; therefore, they should be more innovative. Nevertheless, it is obvious that organizations can have bad performance even if they operate in favourable environment, since the external context has always a remarkable influence, but it cannot completely determine firms' behaviours, decisions and performance.

In sum, the results are quite in line with the aforementioned innovation rankings, and it makes sense that the best results are achieved by Denmark. The only outlier is Brazil, the best country if compared to Denmark, preceding Sweden and Switzerland, with a path coefficient of -0.17, even if the support is weak. Indeed, Brazil does not achieve brilliant performance neither in macro-economic stability nor in good innovation ecosystem, according to the World Economic Forum Report (2019). The reason behind that lies in the data preparation phase, since the final database without missing values used to perform SEM comprehends just one Brazilian company, so it does not make too much sense to generalize the results to all the firms operating there. Therefore, to increase the reliability of this analysis, it should be considered a higher number of enterprises for each country, thus decreasing the dependence from single organization's performance.

6. CONCLUSIONS

Once presented and discussed the outcomes of the performed statistical analyses, this chapter illustrate the final comments and the conclusion of the research.
In detail, the chapter is divided into two sections: (i) implications and (ii) limitations and future researches.

6.1 Implications

This section aims at assessing the contributions of this work, in terms of theoretical implications over the academic scientific literature and managerial implications for the decision-makers of a company. The following sub-sections deeply examine these two aspects.

6.1.1 Theoretical Implications

This thesis provides useful insights to the extant theory, mainly regarding the two principal topics addressed in the literature review – i.e. ambidexterity and I4.0.
In detail, the theoretical implications can be divided into four different contributions.

First of all, the plausible influence that SMTs could have on exploitative-operations and explorative-innovation strategies is questioned, and thus the relationship between SMTs adoption and ambidexterity level achievable by firms.
The outcomes of the statistical tests highlight how I4.0 positively affects the capability of simultaneously pursuing exploitation and exploration strategies within different departments, thus fostering structural ambidexterity.
This represents a remarkable contribution for the academic researchers since, as underlined in the literature review, there is an almost complete absence of papers which simultaneously consider SMTs and ambidexterity, as only few articles recently assessed the role of I4.0 as enabler for structural ambidexterity. In particular, this research is the first empirical analysis which tests this hypothesis in the intra-company context, thus filling a significant literature gap.

Second, the proposed model sheds lights on the contradictory and ambiguous relationship between structural ambidexterity and IP.
As stated in literature review, many authors argue that, if an enterprise wants to excel in both improving existing products and generating new ones, it should apply structural ambidexterity; anyway, no one clearly demonstrates that structural separation positively influences IP, since scholars usually examine ambidexterity in general, without focusing on a particular

configuration – e.g. structural or contextual. Moreover, several investigations assess the relationship between exploitation, exploration and ambidexterity within the same model, but the results are contradictory; indeed, some authors certify positive results, others negative ones, either associated to firms exceeding in one of the two dimensions, or to difficulties in achieving ambidexterity.

The SEM analyses performed over Stata provide support and clarify that, by combining exploitation within the operations function and exploration within the innovation function, companies can increase their IP, thus filling another remarkable literature gap.

Afterwards, the impacts of achieving good financial performance over the ability of an enterprise to invest in innovation and thus obtaining brilliant IP is demonstrated.

As the literature analysis showed, the positive effect of innovation over BP is frequently underlined, since an innovative mindset allows organizations to effectively tackle environmental changes and thereby improve the performance, by creating competitive advantages difficult to be achieved by competitors. However, there’s a lack of works which exhibit the inverse relationship.

In proving this positive connection, this thesis directly answers to the question proposed by Piening and Salge (2015), who suggest to investigate and determine if financial availability positively influence enterprises’ IP. Additionally, the enabling role of monetary performance over SMTs’ adoption is certified, thus proving that organizations should perform well in order to adopt such costly technologies.

This fills another important gap, since the conducted research illustrates how well-performing companies are in a favourable position to implement SMTs and embrace I4.0.

Finally, an innovative way to operationalize ambidexterity in SEM path analysis is proposed. The review of the extant literature has shown the lack of agreement between scholars regarding how to conceive ambidexterity. Indeed, even if there is a broad consensus that ambidextrous organizations engage in both components, it is unclear if these firms’ effort is focused on the combined magnitude of exploitation and exploration, or on matching the magnitude of these two types of activities. This paradoxical vision refers to 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. Nevertheless, as illustrated in the literature, the two alternatives both present remarkable drawbacks. The new proposed formula, 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, including in the computation the sum and the absolute difference between exploit and explore at the same time.
Therefore, this contribution is remarkable since it could help to solve the conflict regarding how to operationalize the interaction between exploitative and explorative strategies.

6.1.2 Managerial Implications

After having defined the theoretical implications, this sub-section illustrates how the performed analyses can provide useful managerial suggestions and thus support the decision-makers of enterprises.

First, the conducted study proves the potential benefits stemming from simultaneously pursuing exploitative and explorative strategies; in particular, the focus is on the structural conception of ambidexterity. As a consequence, top managers should consider the organizational separation as a practicable and reliable solution to make the company ambidextrous and thus to be aligned and efficient in the management of today's business as well as being adaptive to changes in the environment. In particular, this research suggests to exploit within the production function and explore new technological solutions within the innovation one. 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 core business.

Moreover, the performed research sheds lights on a possible enabler of ambidexterity within an enterprise. Indeed, the embracement of I4.0 principles and in particular the adoption of some SMTs is a reliable solution to make an organization more ambidextrous.
In practice, managers should opt for introducing new technological tools – e.g. additive manufacturing, ERP systems, RFId tags, etc. – which will improve the capability of the firm to optimize and standardize the actual production's processes and simultaneously explore new solution to grant brilliant results in the long-term.
In doing that, a first key challenge would be represented by the new tasks that operators should perform; indeed, the employees should deal with innovative procedures and interact with technological tools different from the previous ones. A possible way to solve this issue could be introducing training courses or support the operators by making them working alongside with technological experts. Secondly companies should also consider to undertake some changes in their data acquisition process – i.e. establishing dedicated units for analysing in effective way big data.

Beyond that, useful insights are provided to decision-makers also regarding how to invest money. The study demonstrates how achieving excellent IP is related to the financial availability of the firm; indeed, 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. In particular, given the high cost of adoption and initial implementation of SMTs, financial availability constitutes a strong enabler of I4.0. Therefore, decision-makers should opt for investing money in new breakthrough innovations which, as stated in the previous paragraphs, will grant excellent IP in both short and long-term.

Moreover, the SEM path analysis illustrates how the context which organizations are operating in has a remarkable influence in the possibility of achieving brilliant IP. Indeed, the level of innovation is different country by country, and this affects the accessibility to the SMTs. As a consequence, before wasting the financial assets, decision-makers should evaluate the level of innovation of the industry which the enterprise is operating in.

In conclusion, the statistical analyses reveal a null impact of the company size. This means that all the aforementioned suggestions are valid and effective for managers working in organizations of both small and large dimensions.

Table 27 summarizes the contributions stemming from the addressed research questions.

RESEARCH QUESTION	**SOLUTION**	**THEORETICAL CONTRIBUTION**	**MANAGERIAL CONTRIBUTION**
Do SMTs allow company to be ambidextrous, and thus pursue at the same time exploitative and explorative strategies?	SMTs are a reliable enabler of structural ambidexterity	For the first time it is empirically demonstrated the role of antecedent of SMTs over ambidexterity at the intra-company level	Decision-makers should opt for introducing new technological tools which will foster structural ambidexterity; this procedure should be accompanied by training courses for the operators
Do exploitation, exploration and structural ambidexterity have a positive impact on IP?	Exploit, explore and structural ambidexterity enhance the IP of a firm both in short and long-term	The controversial relationship between ambidexterity and IP is clarified by proving the positive influence of structural ambidexterity over such performance	Structural ambidexterity is a reliable way to enhance IP; in particular, enterprises should create a department to exploit current production's processes and another one to explore new technological solutions
Are well-performing companies, from a financial perspective, in a good position to have greater IP?	Well-performing companies have easier access to SMTs and thus are in a favourable position to improve their IP both in short and long-term	Several articles prove the impact of IP over BP; this research fills a remarkable gap by demonstrating the inverse relationship. Meanwhile, the enabling effect of BP over SMTs' adoption is directly certified for the first time	Decision-makers of firm with financial resources available should push for investing them in SMTs, since they are a reliable antecedent of structural ambidexterity and thus they can indirectly enhance IP

Table 27: Research questions and respective contributions

6.2 Limitations and Future Researches

The conducted study not only leads to some relevant contributions, but it also rises some restrictions of the performed analyses which could be improved in future investigations.
In detail, the following two sub-sections illustrate the limitations and the possible future researches.

6.2.1 Limitations

This thesis relies on a theoretical model, which is defined as a representation or simplified version of a concept, relationship, phenomenon or aspect of the real world; therefore, by definition, a model has to make some simplifications and assumptions. As a consequence, it is clear that every model has some limitations. In detail, the following weakness of the conducted work have been identified.

First of all, as the methodology already anticipated and showed, the main shortcoming of this study is represented by data availability and reliability. Indeed, the starting dataset was affected by incompleteness – i.e. missing values – and noise data – i.e. outliers.
In order to overcome these issues, it has been necessary to implement some procedures of cleaning and validation, which sensibly reduced the number of observations available to test the hypotheses. This is why the proposed model comprehends just sixty-two observations, fact which represents the most critical issue of the performed analyses, since this parameter directly affects the reliability of the empirical tests.
Moreover, the distribution of the empty values was not heterogeneous. This led to an unbalanced final database, since the majority of missing values were concentrated in few countries; as a result, some country had only two or three observations to be tested with the SEM path analysis. Beyond that, another limitation related to the data handling process is constituted by possible biased responses. As far as the survey is concerned, some questions cannot be answered in a subjective way, thus incrementing the possibility of having responses distorted by the interviewees' perception – e.g. questions related to the IP construct.

Additionally, the questions of the survey used to test the BP and IP constructs refer to the same timeframe – i.e. the last three years. Nevertheless, since the theoretical model proposed by this research hypothesizes an enabling role on BP over IP, the items constituting IP should describe the results obtained by the interviewed firms in a period of time subsequent to the BP's one.

This is one of the main limitations, since the IP represented in the model does not exactly reflect the requests of the underlying theory.

Finally, in order to operationalize the company size, the number of people working in the business unit and in the department have been summed. It is clear that this value is a proxy and it does not represent the real organization size. Hence, this assumption represents another limitation.

6.2.2 Future Researches

All the aforementioned limitations can be transformed into possible future investigation, which could enlarge and refine the provided insights.

In this sense, future analyses could first of all interview a higher sample of countries to enable both a more complete assessment about countries positioning and a more reliable statistical analysis, due to the higher data availability. Beyond that, the questions of the survey related to the items which constitute the construct IP could be modified to overcome the temporal limitation described in the previous sub-section.

Once applied these adjustments, it would be interesting to conduct a similar analysis with the same framework in the years ahead to observe whether the hypotheses will still be supported and whether a correlation for the rejected hypothesis can be observed or not.

Other potential streams of research do not stem directly from the limitations, but rather are a way to integrate what has been found within the literature.

Therefore, additional analyses could try to demonstrate some causal relationships which have not been assessed in this thesis. For instance, the direct path between SMT and IP or between SMT and ambidexterity could be added to the model.

Additionally, other investigations could assess the separated impact of each SMT over structural ambidexterity and thus IP; for instance, the consequences 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.

It is also interesting to underline that the extant literature has often linked ambidexterity and companies' performance with environmental dynamism and market turbulence, the amount of investment with the risk aversion mindset of management, and the structural ambidexterity effectiveness with the coordination level within the organization. Therefore, all these topics could be included into the model to enrich the analysis and have a more complete vision of the enterprises' dynamics. In this sense, even other mediators of the relationship between BP and IP could be examined, in order to either support the validity of an already established antecedent of IP or to prove the existence of a new unexplored enabler.

Finally, future studies should also investigate the size's effect by modelling it in a more accurate way, in order to understand whether the findings coming from this research certify a new evidence, or if the outcomes have been biased by how the control variable size has been operationalized.

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APPENDIX

Appendix A – Detailed Stata Code

```
  ___  ____  ____  ____  ____ (R)
 /__    /   ____/   /   ____/
___/   /   /___/   /   /___/   14.2   Copyright 1985-2015 StataCorp LLC
  Statistics/Data Analysis            StataCorp
                                      4905 Lakeway Drive
     Special Edition                  College Station, Texas 77845 USA
                                      800-STATA-PC        http://www.stata.com
                                      979-696-4600        stata@stata.com
                                      979-696-4601 (fax)




Notes:
      1.  Unicode is supported; see help unicode_advice.
      2.  Maximum number of variables is set to 5000; see help set_maxvar.

. sembuilder "C:\Users\Alessandro\Dropbox\Thesis\New Stata\Sem_fin.stsem"

. use "C:\Users\Alessandro\Dropbox\Thesis\New Stata\Final dataset base.dta", clear

. factor BP_1 BP_2 BP_3 SMT_1 SMT_2 SMT_3 SMT_4 SMT_5 EXPLT_1 EXPLT_2 EXPLT_3 EXPLT_4 EXPLR_1 EXPLR_2 EXPLR_4 I
> P_1 IP_2 IP_3 IP_4, factor(5)
(obs=63)

Factor analysis/correlation                     Number of obs    =         63
    Method: principal factors                   Retained factors =          5
    Rotation: (unrotated)                       Number of params =         85
```

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	6.23752	3.97334	0.5115	0.5115
Factor2	2.26418	0.73892	0.1857	0.6972
Factor3	1.52526	0.45434	0.1251	0.8223
Factor4	1.07093	0.40858	0.0878	0.9101
Factor5	0.66235	0.08869	0.0543	0.9644
Factor6	0.57365	0.19319	0.0470	1.0114
Factor7	0.38046	0.18700	0.0312	1.0426
Factor8	0.19347	0.06150	0.0159	1.0585
Factor9	0.13196	0.01060	0.0108	1.0693
Factor10	0.12136	0.11247	0.0100	1.0793
Factor11	0.00889	0.02627	0.0007	1.0800
Factor12	-0.01738	0.02664	-0.0014	1.0786
Factor13	-0.04403	0.04390	-0.0036	1.0750
Factor14	-0.08793	0.02974	-0.0072	1.0677
Factor15	-0.11766	0.01262	-0.0096	1.0581
Factor16	-0.13029	0.03680	-0.0107	1.0474
Factor17	-0.16709	0.00216	-0.0137	1.0337
Factor18	-0.16924	0.07265	-0.0139	1.0198

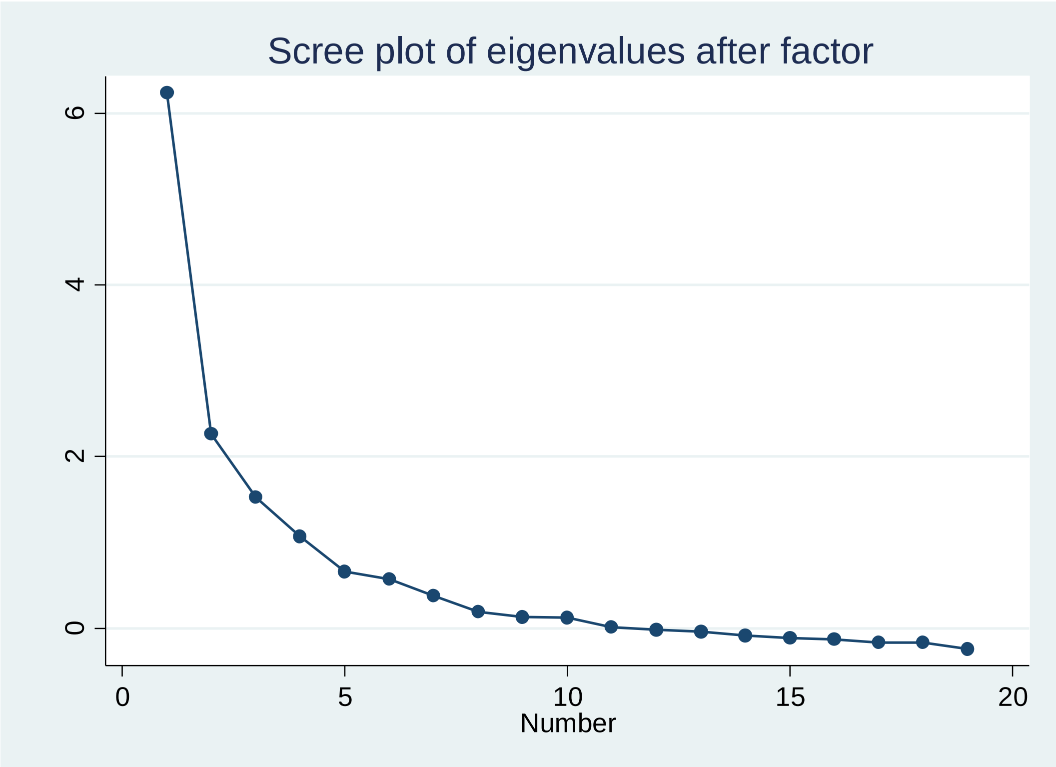
Factor19	-0.24189	.	-0.0198	1.0000

LR test: independent vs. saturated: chi2(171) = 717.84 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Factor4	Factor5	Uniqueness
BP_1	0.5542	0.7218	-0.2353	0.1170	-0.0290	0.1020
BP_2	0.5378	0.6714	-0.3282	0.0335	-0.0295	0.1504
BP_3	0.5396	0.7175	-0.1545	0.0470	-0.1084	0.1562
SMT_1	0.4753	0.2545	0.3884	0.3104	0.1063	0.4509
SMT_2	0.5024	-0.1737	0.3356	0.3547	-0.1589	0.4538
SMT_3	0.3689	-0.0491	0.4649	0.1540	0.1132	0.6089
SMT_4	0.6037	0.0315	0.3086	0.2905	-0.0701	0.4500
SMT_5	0.5522	-0.0371	0.2672	0.1235	0.2911	0.5223
EXPLT_1	0.6720	-0.0295	0.2739	-0.5054	-0.2069	0.1742
EXPLT_2	0.7151	0.0236	0.1324	-0.4119	-0.2210	0.2521
EXPLT_3	0.5964	-0.1810	0.2097	-0.2281	-0.0895	0.5076
EXPLT_4	0.7108	-0.0263	0.1311	-0.2153	0.0412	0.4288
EXPLR_1	0.6212	-0.3768	-0.3369	0.2728	-0.1582	0.2591
EXPLR_2	0.5865	-0.3589	-0.2337	0.2429	-0.1511	0.3907
EXPLR_4	0.5054	-0.5306	-0.3374	0.1329	-0.1952	0.2934
IP_1	0.6056	-0.1412	-0.0634	-0.1080	0.3969	0.4401
IP_2	0.6239	-0.1159	-0.1250	-0.0822	0.2840	0.4942
IP_3	0.6547	-0.1854	-0.3845	-0.0705	0.1178	0.3703
IP_4	0.2694	-0.1515	-0.2983	-0.1017	0.2655	0.7347

. screeplot



```
. rotate, promax

Factor analysis/correlation                        Number of obs    =         63
    Method: principal factors                      Retained factors =          5
    Rotation: oblique promax (Kaiser off)          Number of params =         85
```

Factor	Variance	Proportion	Rotated factors are correlated
Factor1	4.41543	0.3621	
Factor2	4.00888	0.3287	
Factor3	3.79197	0.3110	
Factor4	3.52116	0.2887	
Factor5	3.46362	0.2840	

```
    LR test: independent vs. saturated: chi2(171) =  717.84 Prob>chi2 = 0.0000
```

Rotated factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Factor4	Factor5	Uniqueness
BP_1	-0.0453	0.0160	-0.0034	0.0781	0.9346	0.1020
BP_2	0.0038	0.0537	0.0331	-0.0663	0.9106	0.1504
BP_3	0.1035	-0.0864	-0.0443	0.0686	0.8961	0.1562
SMT_1	-0.1035	0.0784	-0.1337	0.7020	0.2171	0.4509
SMT_2	0.0317	-0.1742	0.3206	0.6542	-0.0705	0.4538
SMT_3	0.0620	0.1245	-0.1320	0.6004	-0.1508	0.6089
SMT_4	0.0533	-0.0519	0.1703	0.6283	0.1220	0.4500
SMT_5	-0.0361	0.4343	-0.0823	0.5008	-0.0495	0.5223
EXPLT_1	0.9737	-0.0242	-0.0851	-0.0374	-0.0154	0.1742
EXPLT_2	0.8453	-0.0310	0.0423	-0.0610	0.1277	0.2521
EXPLT_3	0.5714	0.0805	0.0880	0.1274	-0.1199	0.5076
EXPLT_4	0.4742	0.2600	0.0160	0.1317	0.0581	0.4288
EXPLR_1	-0.0855	0.0342	0.8370	0.0966	0.0616	0.2591
EXPLR_2	-0.0330	0.0176	0.7338	0.1445	0.0154	0.3907
EXPLR_4	0.0524	0.0111	0.8355	-0.0568	-0.1257	0.2934
IP_1	0.0339	0.7056	0.0111	0.0881	-0.0494	0.4401
IP_2	0.0620	0.5732	0.1206	0.0499	0.0366	0.4942
IP_3	0.0742	0.4334	0.4312	-0.1594	0.1379	0.3703
IP_4	-0.0828	0.5001	0.1385	-0.2014	-0.0123	0.7347

Factor rotation matrix

	Factor1	Factor2	Factor3	Factor4	Factor5
Factor1	0.2592	-0.1938	-0.4187	0.6229	-0.2894
Factor2	-0.2185	0.5694	-0.2338	0.0280	-0.0546
Factor3	-0.0650	-0.1394	-0.5115	0.0339	0.7668
Factor4	-0.4864	-0.1798	0.2308	0.4125	0.0711
Factor5	0.8026	0.7658	0.6746	0.6633	0.5658

```
. sortl

Rotated factor loadings (pattern matrix) and unique variances sorted
```

Variable	Factor1	Factor2	Factor3	Factor4	Factor5	Uniqueness
EXPLT_1	0.9737	-0.0242	-0.0851	-0.0374	-0.0154	0.1742
EXPLT_2	0.8453	-0.0310	0.0423	-0.0610	0.1277	0.2521
EXPLT_3	0.5714	0.0805	0.0880	0.1274	-0.1199	0.5076
EXPLT_4	0.4742	0.2600	0.0160	0.1317	0.0581	0.4288
IP_1	0.0339	0.7056	0.0111	0.0881	-0.0494	0.4401
IP_2	0.0620	0.5732	0.1206	0.0499	0.0366	0.4942
IP_4	-0.0828	0.5001	0.1385	-0.2014	-0.0123	0.7347
IP_3	0.0742	0.4334	0.4312	-0.1594	0.1379	0.3703
EXPLR_1	-0.0855	0.0342	0.8370	0.0966	0.0616	0.2591
EXPLR_4	0.0524	0.0111	0.8355	-0.0568	-0.1257	0.2934
EXPLR_2	-0.0330	0.0176	0.7338	0.1445	0.0154	0.3907
SMT_1	-0.1035	0.0784	-0.1337	0.7020	0.2171	0.4509
SMT_2	0.0317	-0.1742	0.3206	0.6542	-0.0705	0.4538
SMT_4	0.0533	-0.0519	0.1703	0.6283	0.1220	0.4500
SMT_3	0.0620	0.1245	-0.1320	0.6004	-0.1508	0.6089
SMT_5	-0.0361	0.4343	-0.0823	0.5008	-0.0495	0.5223
BP_1	-0.0453	0.0160	-0.0034	0.0781	0.9346	0.1020
BP_2	0.0038	0.0537	0.0331	-0.0663	0.9106	0.1504
BP_3	0.1035	-0.0864	-0.0443	0.0686	0.8961	0.1562

```
. alpha BP_1 BP_2 BP_3

Test scale = mean(unstandardized items)

Average interitem covariance:     .7404102
Number of items in the scale:            3
Scale reliability coefficient:      0.9276

.
. alpha SMT_1 SMT_2 SMT_3 SMT_4 SMT_5

Test scale = mean(unstandardized items)

Average interitem covariance:      .572174
Number of items in the scale:            5
Scale reliability coefficient:      0.7119

.
. alpha EXPLT_1 EXPLT_2 EXPLT_3 EXPLT_4

Test scale = mean(unstandardized items)

Average interitem covariance:     .4915299
Number of items in the scale:            4
Scale reliability coefficient:      0.8256
```

```
.
. alpha EXPLR_1 EXPLR_2 EXPLR_3 EXPLR_4

Test scale = mean(unstandardized items)

Average interitem covariance:      .479938
Number of items in the scale:            4
Scale reliability coefficient:      0.7616

.
. alpha IP_1 IP_2 IP_3 IP_4

Test scale = mean(unstandardized items)

Average interitem covariance:     .3217252
Number of items in the scale:            4
Scale reliability coefficient:      0.6746

. sem (EXPLR -> EXPLR_1, ) (EXPLR -> EXPLR_2, ) (EXPLR -> EXPLR_3, ) (EXPLR -> EXPLR_4, ) (EXPLR -> InnPerf, )
> (BussPerf -> BP_1, ) (BussPerf -> BP_2, ) (BussPerf -> BP_3, ) (BussPerf -> SMT, ) (SMT -> EXPLR, ) (SMT -> S
> MT_1, ) (SMT -> EXPLT, ) (SMT -> SMT_2, ) (SMT -> SMT_3, ) (SMT -> SMT_4, ) (SMT -> SMT_5, ) (EXPLT -> EXPLT_
> 1, ) (EXPLT -> EXPLT_2, ) (EXPLT -> EXPLT_3, ) (EXPLT -> EXPLT_4, ) (EXPLT -> InnPerf, ) (InnPerf -> IP_1, )
> (InnPerf -> IP_2, ) (InnPerf -> IP_3, ) (InnPerf -> IP_4, ) (Size -> InnPerf, ) (Canada -> InnPerf, ) (Hungar
> y -> InnPerf, ) (Italy -> InnPerf, ) (Pakistan -> InnPerf, ) (Spain -> InnPerf, ) (Sweden -> InnPerf, ) (Swit
> z -> InnPerf, ) (Brazil -> InnPerf, ), covstruct(_lexogenous, diagonal) cov(_lexogenous*_oexogenous@0) latent
> (EXPLR BussPerf SMT EXPLT InnPerf ) nocapslatent
(127 observations with missing values excluded)
Endogenous variables

Measurement:  EXPLR_1 EXPLR_2 EXPLR_3 EXPLR_4 BP_1 BP_2 BP_3 SMT_1 SMT_2 SMT_3 SMT_4 SMT_5 EXPLT_1 EXPLT_2
              EXPLT_3 EXPLT_4 IP_1 IP_2 IP_3 IP_4
Latent:       EXPLR InnPerf SMT EXPLT

Exogenous variables

Observed:     Size Canada Hungary Italy Pakistan Spain Sweden Switz Brazil
Latent:       BussPerf

Fitting target model:

Iteration 0:   log likelihood = -2167.2641  (not concave)
Iteration 1:   log likelihood = -2154.2165  (not concave)
Iteration 2:   log likelihood = -2125.6145  (not concave)
Iteration 3:   log likelihood = -2088.2766  (not concave)
Iteration 4:   log likelihood =  -2071.549
Iteration 5:   log likelihood = -2065.5532
Iteration 6:   log likelihood = -2064.0925
Iteration 7:   log likelihood = -2064.0563
Iteration 8:   log likelihood = -2064.0562

Structural equation model                      Number of obs     =         62
Estimation method  = ml
Log likelihood     = -2064.0562

 ( 1)  [EXPLR_1]EXPLR = 1
 ( 2)  [SMT_1]SMT = 1
 ( 3)  [EXPLT_1]EXPLT = 1
 ( 4)  [IP_1]InnPerf = 1
 ( 5)  [BP_1]BussPerf = 1
```

	Coef.	OIM Std. Err.	z	P>|z|	[95% Conf.	Interval]
Structural						
EXPLR <-						
SMT	.4356674	.1614767	2.70	0.007	.1191788	.752156
InnPerf <-						
EXPLR	.3487511	.1076208	3.24	0.001	.1378182	.559684
EXPLT	.3737373	.108565	3.44	0.001	.1609538	.5865208
Size	5.42e-06	.0000158	0.34	0.732	-.0000256	.0000364
Canada	-1.296728	.4439835	-2.92	0.003	-2.16692	-.4265362
Hungary	-.5587928	.3510128	-1.59	0.111	-1.246765	.1291796
Italy	-.8046733	.3119759	-2.58	0.010	-1.416135	-.1932118
Pakistan	-.3423174	.2758639	-1.24	0.215	-.8830006	.1983659
Spain	-.4975995	.2849818	-1.75	0.081	-1.056153	.0609545
Sweden	-.33304	.4039373	-0.82	0.410	-1.124743	.4586627
Switz	-.4174281	.3101401	-1.35	0.178	-1.025292	.1904352
Brazil	-.6160023	.5041841	-1.22	0.222	-1.604185	.3721803
SMT <-						
BussPerf	.3658136	.1305295	2.80	0.005	.1099804	.6216468
EXPLT <-						
SMT	.7160076	.1874025	3.82	0.000	.3487055	1.08331
Measurement						
EXPLR_1 <-						
EXPLR	1	(constrained)				
_cons	3.790322	.1143618	33.14	0.000	3.566177	4.014467
EXPLR_2 <-						
EXPLR	.8966072	.1267427	7.07	0.000	.648196	1.145018
_cons	3.83871	.1189478	32.27	0.000	3.605576	4.071843
EXPLR_3 <-						
EXPLR	.8002542	.1216318	6.58	0.000	.5618602	1.038648
_cons	3.790322	.1143618	33.14	0.000	3.566178	4.014467
EXPLR_4 <-						
EXPLR	.9050929	.1309467	6.91	0.000	.648442	1.161744
_cons	3.596774	.1279383	28.11	0.000	3.34602	3.847528
BP_1 <-						
BussPerf	1	(constrained)				
_cons	3.403226	.1334129	25.51	0.000	3.141741	3.66471
BP_2 <-						
BussPerf	.9189967	.0667365	13.77	0.000	.7881956	1.049798
_cons	3.467742	.1299719	26.68	0.000	3.213002	3.722482
BP_3 <-						
BussPerf	.946721	.0757735	12.49	0.000	.7982077	1.095234
_cons	3.306452	.1375017	24.05	0.000	3.036953	3.57595

SMT_1 <-						
SMT	1	(constrained)				
_cons	3.467742	.1687281	20.55	0.000	3.137041	3.798443
SMT_2 <-						
SMT	.789467	.205936	3.83	0.000	.3858399	1.193094
_cons	3.677419	.1401912	26.23	0.000	3.402649	3.952189
SMT_3 <-						
SMT	.8285055	.2455573	3.37	0.001	.3472219	1.309789
_cons	3.225806	.1728433	18.66	0.000	2.88704	3.564573
SMT_4 <-						
SMT	.9709203	.2220695	4.37	0.000	.5356722	1.406169
_cons	2.693548	.1435188	18.77	0.000	2.412256	2.97484
SMT_5 <-						
SMT	.9363336	.2384896	3.93	0.000	.4689026	1.403765
_cons	2.629032	.164854	15.95	0.000	2.305924	2.95214
EXPLT_1 <-						
EXPLT	1	(constrained)				
_cons	3.919355	.1276099	30.71	0.000	3.669244	4.169465
EXPLT_2 <-						
EXPLT	.9627113	.1006108	9.57	0.000	.7655177	1.159905
_cons	3.774193	.1278562	29.52	0.000	3.5236	4.024787
EXPLT_3 <-						
EXPLT	.6748828	.1182351	5.71	0.000	.4431463	.9066193
_cons	3.677419	.1202109	30.59	0.000	3.44181	3.913028
EXPLT_4 <-						
EXPLT	.6179239	.0986323	6.26	0.000	.4246082	.8112396
_cons	3.951613	.1030932	38.33	0.000	3.749554	4.153672
IP_1 <-						
InnPerf	1	(constrained)				
_cons	3.825854	.283685	13.49	0.000	3.269842	4.381866
IP_2 <-						
InnPerf	1.106906	.2409738	4.59	0.000	.6346057	1.579206
_cons	4.26503	.3106427	13.73	0.000	3.656181	4.873878
IP_3 <-						
InnPerf	1.206913	.2543992	4.74	0.000	.7082999	1.705526
_cons	4.071812	.3315362	12.28	0.000	3.422013	4.721611
IP_4 <-						
InnPerf	.6658699	.2817586	2.36	0.018	.1136333	1.218106
_cons	3.40502	.2559885	13.30	0.000	2.903292	3.906748
var(e.EXPLR_1)	.1425499	.0578227			.0643714	.3156754
var(e.EXPLR_2)	.3399423	.0803209			.2139366	.5401638
var(e.EXPLR_3)	.3828747	.0802477			.2538933	.5773806
var(e.EXPLR_4)	.4673417	.0972573			.3108088	.7027096

```
    var(e.BP_1)     .06876   .0387389                              .0227916     .207442
    var(e.BP_2)   .1734196   .0434085                              .1061781    .2832446
    var(e.BP_3)    .244765   .0560764                              .1562199    .3834973
   var(e.SMT_1)   1.045766   .2260931                              .6845512    1.597581
   var(e.SMT_2)   .7701987   .1604147                              .5120555     1.15848
   var(e.SMT_3)   1.358479   .2667046                              .9245703    1.996024
   var(e.SMT_4)   .5989595   .1459168                               .371561    .9655278
   var(e.SMT_5)   1.054319   .2211631                              .6989021    1.590477
 var(e.EXPLT_1)   .1815575   .0611406                              .0938354    .3512865
 var(e.EXPLT_2)   .2460635   .0646223                              .1470621     .411712
 var(e.EXPLT_3)   .5187843   .1014079                              .3536719    .7609796
 var(e.EXPLT_4)   .3427679   .0688739                              .2311875    .5082014
    var(e.IP_1)    .595305   .1211974                              .3994335    .8872268
    var(e.IP_2)   .3255591   .0806949                               .200284    .5291922
    var(e.IP_3)   .2905262   .0802186                              .1691048    .4991312
    var(e.IP_4)   1.264654    .233402                              .8807969    1.815799
   var(e.EXPLR)   .5317924   .1310316                              .3281024    .8619358
 var(e.InnPerf)   .0829361   .0475942                               .026932    .2553989
     var(e.SMT)   .5808488   .2297905                              .2674964    1.261271
   var(e.EXPLT)    .459295   .1328013                              .2605996    .8094864
  var(BussPerf)   1.034778    .201195                              .7068797    1.514777

LR test of model vs. saturated: chi2(336) =    524.20, Prob > chi2 = 0.0000

. estat gof, stats(all)
```

Fit statistic	Value	Description
Likelihood ratio		
chi2_ms(336)	524.199	model vs. saturated
p > chi2	0.000	
chi2_bs(370)	1169.006	baseline vs. saturated
p > chi2	0.000	
Population error		
RMSEA	0.095	Root mean squared error of approximation
90% CI, lower bound	0.079	
upper bound	0.110	
pclose	0.000	Probability RMSEA <= 0.05
Information criteria		
AIC	4276.112	Akaike's information criterion
BIC	4433.520	Bayesian information criterion
Baseline comparison		
CFI	0.764	Comparative fit index
TLI	0.741	Tucker-Lewis index
Size of residuals		
SRMR	0.110	Standardized root mean squared residual
CD	0.978	Coefficient of determination

```
. predict Lexplt Lexplr, latent(EXPLT EXPLR)

.
. egen ZLexplt=std(Lexplt)
```

```
.
. egen ZLexplr=std(Lexplr)

.
. gen exploit_plus=ZLexplt+7

.
. gen explore_plus=ZLexplr+7

.
. gen ZDIFF=abs(ZLexplt-ZLexplr)

.
. gen Amb=(exploit_plus+explore_plus)/(ZDIFF+1)

.
. cor ZLexplt ZLexplr Amb
(obs=189)

             |  ZLexplt  ZLexplr      Amb
-------------+---------------------------
     ZLexplt |   1.0000
     ZLexplr |   0.2137   1.0000
         Amb |   0.3521   0.3435   1.0000

. sem (EXPLR -> EXPLR_1, ) (EXPLR -> EXPLR_2, ) (EXPLR -> EXPLR_3, ) (EXPLR -> EXPLR_4, ) (EXPLR -> InnPerf, )
> (BussPerf -> BP_1, ) (BussPerf -> BP_2, ) (BussPerf -> BP_3, ) (BussPerf -> SMT, ) (SMT -> EXPLR, ) (SMT -> S
> MT_1, ) (SMT -> EXPLT, ) (SMT -> SMT_2, ) (SMT -> SMT_3, ) (SMT -> SMT_4, ) (SMT -> SMT_5, ) (EXPLT -> EXPLT_
> 1, ) (EXPLT -> EXPLT_2, ) (EXPLT -> EXPLT_3, ) (EXPLT -> EXPLT_4, ) (EXPLT -> InnPerf, ) (InnPerf -> IP_1, )
> (InnPerf -> IP_2, ) (InnPerf -> IP_3, ) (InnPerf -> IP_4, ) (Size -> InnPerf, ) (Canada -> InnPerf, ) (Hungar
> y -> InnPerf, ) (Italy -> InnPerf, ) (Pakistan -> InnPerf, ) (Spain -> InnPerf, ) (Sweden -> InnPerf, ) (Swit
> z -> InnPerf, ) (Brazil -> InnPerf, ) (Amb -> InnPerf, ), covstruct(_lexogenous, diagonal) cov(_lexogenous*_o
> exogenous@0) latent(EXPLR BussPerf SMT EXPLT InnPerf ) nocapslatent
(127 observations with missing values excluded)

Endogenous variables

Measurement:  EXPLR_1 EXPLR_2 EXPLR_3 EXPLR_4 BP_1 BP_2 BP_3 SMT_1 SMT_2 SMT_3 SMT_4 SMT_5 EXPLT_1 EXPLT_2
              EXPLT_3 EXPLT_4 IP_1 IP_2 IP_3 IP_4
Latent:       EXPLR InnPerf SMT EXPLT

Exogenous variables

Observed:     Size Canada Hungary Italy Pakistan Spain Sweden Switz Brazil Amb
Latent:       BussPerf

Fitting target model:

Iteration 0:   log likelihood = -2307.0256  (not concave)
Iteration 1:   log likelihood = -2294.0992  (not concave)
Iteration 2:   log likelihood = -2264.5324  (not concave)
Iteration 3:   log likelihood = -2246.7734  (not concave)
Iteration 4:   log likelihood = -2219.1309
Iteration 5:   log likelihood = -2213.4721
Iteration 6:   log likelihood =  -2204.894
Iteration 7:   log likelihood = -2203.3006
Iteration 8:   log likelihood = -2203.2179
Iteration 9:   log likelihood = -2203.2172
Iteration 10:  log likelihood = -2203.2172

Structural equation model                       Number of obs     =         62
Estimation method  = ml
```

```
Log likelihood     = -2203.2172

 ( 1)  [EXPLR_1]EXPLR = 1
 ( 2)  [SMT_1]SMT = 1
 ( 3)  [EXPLT_1]EXPLT = 1
 ( 4)  [IP_1]InnPerf = 1
 ( 5)  [BP_1]BussPerf = 1
------------------------------------------------------------------------------
             |                 OIM
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Structural   |
  EXPLR <-   |
         SMT |   .4334402   .1623724     2.67   0.008     .1151961    .7516844
  -----------+----------------------------------------------------------------
  InnPerf <- |
       EXPLR |   .2655339   .0858227     3.09   0.002     .0973246    .4337433
       EXPLT |   .3017044   .0889788     3.39   0.001     .1273091    .4760996
        Size |   1.73e-06   .0000129     0.13   0.894    -.0000236     .000027
      Canada |  -1.371594   .3870672    -3.54   0.000    -2.130231   -.6129558
     Hungary |  -.7691379   .3003939    -2.56   0.010    -1.357899   -.1803766
       Italy |  -.9759908   .2776193    -3.52   0.000    -1.520115   -.4318668
    Pakistan |  -.6186237   .2430831    -2.54   0.011    -1.095058   -.1421896
       Spain |  -.8326625   .2636504    -3.16   0.002    -1.349408   -.3159171
      Sweden |  -.8363915   .3614765    -2.31   0.021    -1.544872   -.1279106
      Switz  |  -.6238817   .2639093    -2.36   0.018    -1.141134   -.1066291
      Brazil |  -.7377106    .420702    -1.75   0.080    -1.562271    .0868501
         Amb |   .0922964   .0234784     3.93   0.000     .0462795    .1383132
  -----------+----------------------------------------------------------------
  SMT <-     |
    BussPerf |   .3656256   .1307696     2.80   0.005     .1093218    .6219293
  -----------+----------------------------------------------------------------
  EXPLT <-   |
         SMT |    .708705   .1871938     3.79   0.000      .341812    1.075598
-------------+----------------------------------------------------------------
Measurement  |
  EXPLR_1 <- |
       EXPLR |          1  (constrained)
       _cons |   3.790323   .1143618    33.14   0.000     3.566178    4.014468
  -----------+----------------------------------------------------------------
  EXPLR_2 <- |
       EXPLR |   .8836562   .1268733     6.96   0.000     .6349891    1.132323
       _cons |    3.83871   .1189478    32.27   0.000     3.605576    4.071843
  -----------+----------------------------------------------------------------
  EXPLR_3 <- |
       EXPLR |   .7909378   .1209473     6.54   0.000     .5538855     1.02799
       _cons |   3.790323   .1143618    33.14   0.000     3.566178    4.014468
  -----------+----------------------------------------------------------------
  EXPLR_4 <- |
       EXPLR |   .8937501   .1294925     6.90   0.000     .6399495    1.147551
       _cons |   3.596774   .1279383    28.11   0.000      3.34602    3.847529
  -----------+----------------------------------------------------------------
  BP_1 <-    |
    BussPerf |          1  (constrained)
       _cons |   3.403226   .1334129    25.51   0.000     3.141741     3.66471
  -----------+----------------------------------------------------------------
```

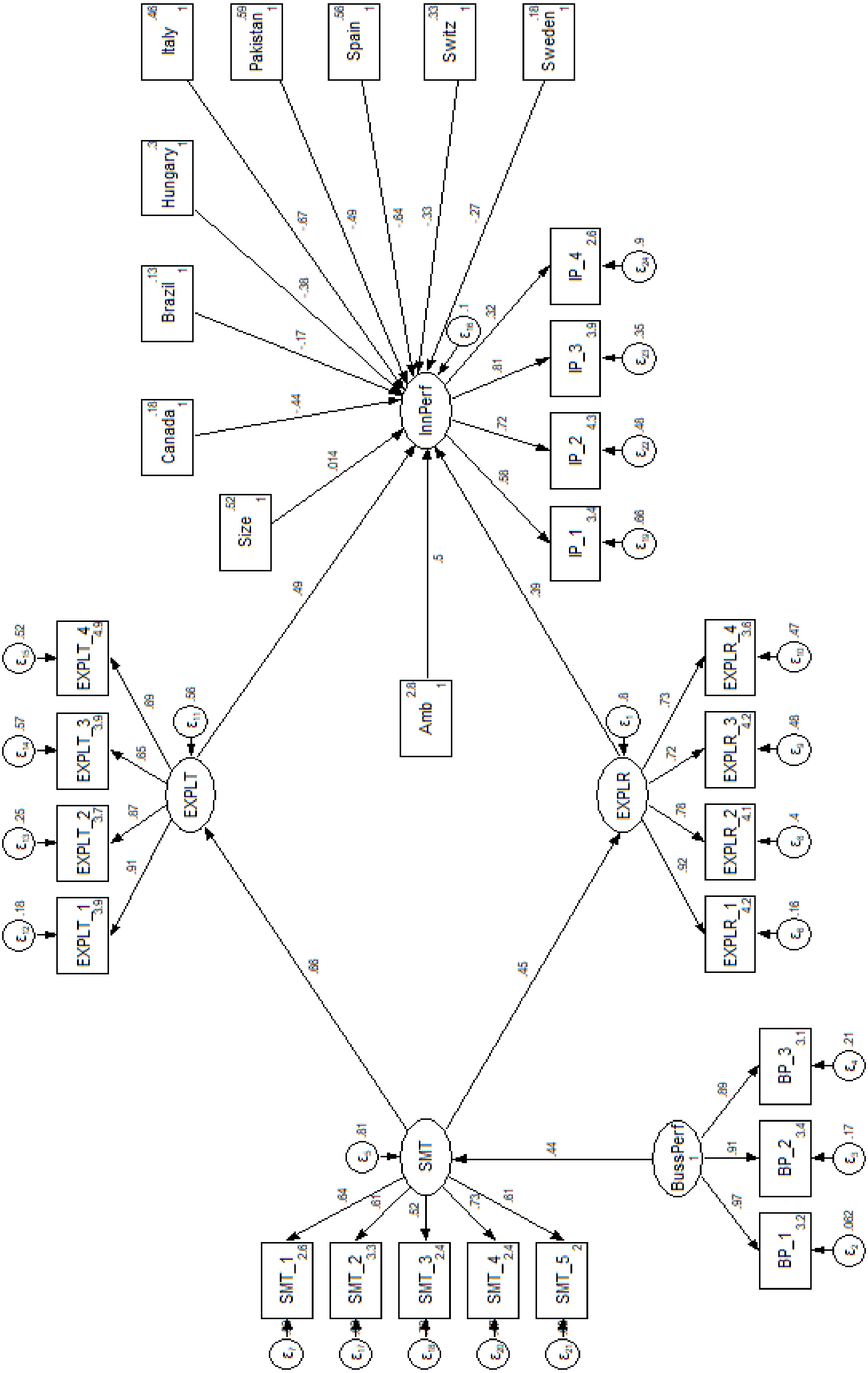
BP_2 <-						
BussPerf	.9191526	.0667421	13.77	0.000	.7883404	1.049965
_cons	3.467742	.1299719	26.68	0.000	3.213002	3.722482
BP_3 <-						
BussPerf	.9468008	.0757731	12.50	0.000	.7982881	1.095313
_cons	3.306452	.1375017	24.05	0.000	3.036953	3.57595
SMT_1 <-						
SMT	1	(constrained)				
_cons	3.467742	.1687281	20.55	0.000	3.137041	3.798443
SMT_2 <-						
SMT	.7947929	.2067	3.85	0.000	.3896684	1.199917
_cons	3.677419	.1401913	26.23	0.000	3.40265	3.952189
SMT_3 <-						
SMT	.8268552	.2455169	3.37	0.001	.345651	1.308059
_cons	3.225806	.1728433	18.66	0.000	2.88704	3.564573
SMT_4 <-						
SMT	.9694718	.2220789	4.37	0.000	.5342051	1.404739
_cons	2.693548	.1435189	18.77	0.000	2.412257	2.97484
SMT_5 <-						
SMT	.9306378	.2379387	3.91	0.000	.4642866	1.396989
_cons	2.629032	.164854	15.95	0.000	2.305924	2.95214
EXPLT_1 <-						
EXPLT	1	(constrained)				
_cons	3.919355	.1276099	30.71	0.000	3.669244	4.169466
EXPLT_2 <-						
EXPLT	.9586896	.1003181	9.56	0.000	.7620697	1.15531
_cons	3.774194	.1278562	29.52	0.000	3.5236	4.024787
EXPLT_3 <-						
EXPLT	.6785752	.1181363	5.74	0.000	.4470324	.9101181
_cons	3.677419	.120211	30.59	0.000	3.44181	3.913028
EXPLT_4 <-						
EXPLT	.6180038	.0985316	6.27	0.000	.4248855	.8111221
_cons	3.951613	.1030932	38.33	0.000	3.749554	4.153672
IP_1 <-						
InnPerf	1	(constrained)				
_cons	3.289909	.2588733	12.71	0.000	2.782527	3.797291
IP_2 <-						
InnPerf	1.105336	.2377107	4.65	0.000	.6394319	1.571241
_cons	3.671865	.2731451	13.44	0.000	3.136511	4.20722
IP_3 <-						
InnPerf	1.260349	.2536866	4.97	0.000	.7631323	1.757566
_cons	3.422365	.3070502	11.15	0.000	2.820558	4.024173

IP_4 <-						
InnPerf	.671294	.2810841	2.39	0.017	.1203793	1.222209
_cons	3.047886	.214901	14.18	0.000	2.626687	3.469084
var(e.EXPLR_1)	.1316111	.0585703			.0550156	.3148465
var(e.EXPLR_2)	.3468099	.0823045			.2178138	.5522016
var(e.EXPLR_3)	.385939	.0807435			.2561156	.581569
var(e.EXPLR_4)	.4722404	.0973226			.3153128	.7072691
var(e.BP_1)	.0689122	.0387357			.0228999	.207376
var(e.BP_2)	.1732517	.0434006			.1060343	.2830796
var(e.BP_3)	.2447451	.0560461			.1562395	.3833869
var(e.SMT_1)	1.044855	.2263948			.6833153	1.597683
var(e.SMT_2)	.7635537	.1598568			.5065624	1.150923
var(e.SMT_3)	1.359821	.2670723			.9253448	1.998296
var(e.SMT_4)	.6001251	.1462922			.372173	.9676955
var(e.SMT_5)	1.061179	.2221267			.7040677	1.59942
var(e.EXPLT_1)	.1787882	.0611925			.0914123	.3496819
var(e.EXPLT_2)	.2499169	.0650013			.1501085	.4160888
var(e.EXPLT_3)	.5133708	.1008806			.3492727	.7545668
var(e.EXPLT_4)	.3416285	.0687967			.2302184	.5069533
var(e.IP_1)	.6085921	.1189828			.4148701	.8927718
var(e.IP_2)	.3430836	.075766			.2225471	.5289054
var(e.IP_3)	.2627756	.0676026			.1587091	.4350791
var(e.IP_4)	1.267955	.2317143			.8862369	1.814086
var(e.EXPLR)	.5439524	.1325689			.3373736	.8770225
var(e.InnPerf)	.0319143	.0296301			.0051726	.1969077
var(e.SMT)	.5819228	.2302451			.2679642	1.263729
var(e.EXPLT)	.4690906	.1339986			.267982	.8211221
var(BussPerf)	1.034626	.201191			.7067415	1.514628

LR test of model vs. saturated: chi2(355) = 552.64, Prob > chi2 = 0.0000

. estat gof, stats(all)

Fit statistic	Value	Description
Likelihood ratio		
chi2_ms(355)	552.643	model vs. saturated
p > chi2	0.000	
chi2_bs(390)	1219.407	baseline vs. saturated
p > chi2	0.000	
Population error		
RMSEA	0.095	Root mean squared error of approximation
90% CI, lower bound	0.079	
upper bound	0.110	
pclose	0.000	Probability RMSEA <= 0.05
Information criteria		
AIC	4556.434	Akaike's information criterion
BIC	4715.969	Bayesian information criterion
Baseline comparison		
CFI	0.762	Comparative fit index
TLI	0.738	Tucker-Lewis index
Size of residuals		
SRMR	0.119	Standardized root mean squared residual
CD	0.992	Coefficient of determination


Italy
Pakistan
Spain
Switz
Sweden
Hungary
Brazil
Canada
Size
Amb
InnPerf
IP_1
IP_2
IP_3
IP_4
EXPLT
EXPLT_1
EXPLT_2
EXPLT_3
EXPLT_4
EXPLR
EXPLR_1
EXPLR_2
EXPLR_3
EXPLR_4
SMT
SMT_1
SMT_2
SMT_3
SMT_4
SMT_5
BussPerf
BP_1
BP_2
BP_3
.88
.45
.49
.39
.5
.44
.014
-.44
-.17
-.38
-.67
-.49
-.64
-.33
-.27

Appendix B – Survey

The present attached aims at showing all the questions of the survey that were used in order to draw the model.

BUSINESS UNIT

Company name, origin, size

Indicate the name, country of origin, main product and size of the business unit your department belongs to	
1. Name	____________________
2. Origin (headquarters' country)	____________________
3. Main product	____________________
4. Business unit size (# of employees in 2015)	__________

Department size

Indicate the size of your department	
5. Business unit size (# of employees in 2015)	__________

Business performance

	Our performance during the past fiscal year was					Our *average* performance relative to our main competitors over the past three years was				
	< 10 Million €	10-50 Million €	50-100 Million €	100-500 Million €	> 500 Million €	Much lower		Equal		Much higher
6. Sales	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
	< 0%	0-5%	5-10%	10-20%	> 20%					
7. Sales growth	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
8. Net profit	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
9. Profit growth	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
10. Return on sales (ROS)	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
11. Domestic market share		☐	☐	☐	☐	☐	☐	☐	☐	☐
12. Global market share		☐	☐	☐	☐	☐	☐	☐	☐	☐
13. Customer satisfaction and loyalty						☐	☐	☐	☐	☐

Production

Production tools and techniques

In our company, the degree of use of the following tools, techniques and systems is	Low				High
14. Computer-aided process planning (CAPP)	☐	☐	☐	☐	☐
15. Industrial robots for machining and/or handling operations	☐	☐	☐	☐	☐
16. Automated materials storage and retrieval systems (AS/RS)	☐	☐	☐	☐	☐
17. Just-in-time (Kanban controlled) production (JIT)					
18. Automatic identification/bar code systems/RFID	☐	☐	☐	☐	☐
19. Total quality management systems (TQM)					
20. "Smart" ICT applications supporting supplier/customer collaboration, connectivity (plants, equipment, robots, lines, workers), data processing (big data)/information mining, modeling/simulation	☐	☐	☐	☐	☐
21. Manufacturing resource planning (MRP II) / enterprise resource planning (ERP)	☐	☐	☐	☐	☐
22. Computer numerically controlled machines tools (CNC)	☐	☐	☐	☐	☐
23. Flexible manufacturing and/or assembly systems (FMS/FAS)	☐	☐	☐	☐	☐
24. Total productive maintenance (TPM)	☐	☐	☐	☐	☐
25. Computer-aided testing systems (CAT)	☐	☐	☐	☐	☐
26. Continuous improvement (CI)/kaizen	☐	☐	☐	☐	☐
27. Advanced/"smart" production technologies (e.g. water and photonics-based/laser cutting, mechatronics, additive manufacturing/3D printing, high precision technologies, micro/nano-processing)	☐	☐	☐	☐	☐
28. Benchmarking/self-assessment (e.g. quality awards, EFQM model)	☐	☐	☐	☐	☐
29. Enterprise risk management (ERM)	☐	☐	☐	☐	☐

Production innovation/improvement practices

In our production function, we systematically	Strongly disagree				Strongly agree
30. Strengthen and upgrade current knowledge and skills for familiar production processes and technologies	☐	☐	☐	☐	☐
31. Invest in incrementally improved equipment, tools and techniques to improve the performance of our production processes	☐	☐	☐	☐	☐
32. Acquire state-of-the-art production knowledge, skills, equipment, tools and techniques	☐	☐	☐	☐	☐
33. Acquire new managerial and organizational skills that are important for production	☐	☐	☐	☐	☐
34. Use clear project targets, project phase standards and project	☐	☐	☐	☐	☐

	managing regulations for our production innovation/improvement activities					
35.	Support and encourage creativity, inventiveness and participation in process innovation and improvement	☐	☐	☐	☐	☐
36.	Invite and use feedback and ideas from external partners (customers, suppliers, research institutes) to improve our production practices and performance	☐	☐	☐	☐	☐
37.	Adapt to environmental changes easily and quickly by innovating and improving our production processes	☐	☐	☐	☐	☐
38.	Use mechanisms such as kaizen, improvement teams and incentives to systematically and continuously improve our performance	☐	☐	☐	☐	☐

New product development

Innovation/improvement practices

In our innovation function, we systematically		Strongly disagree				Strongly agree
1.	Strengthen and upgrade current knowledge and skills for familiar products and technologies	☐	☐	☐	☐	☐
2.	Invest in incrementally improved equipment, tools and techniques to improve the performance of our product development processes	☐	☐	☐	☐	☐
3.	Acquire state-of-the-art product development knowledge, skills, equipment, tools and techniques	☐	☐	☐	☐	☐
4.	Acquire new managerial and organizational skills that are important for our product development processes	☐	☐	☐	☐	☐
5.	Involve marketing, purchasing and production in the front end stages of product development (opportunity identification, ideation, concept development)	☐	☐	☐	☐	☐
6.	Involve marketing, purchasing and production in the back end stages of product development (product design, prototyping, test)	☐	☐	☐	☐	☐
7.	Involve marketing, purchasing and production in the new product introduction process (process design, pilot production, production launch)	☐	☐	☐	☐	☐
8.	Use clear project targets, project phase standards and project management regulations for our new product development activities	☐	☐	☐	☐	☐
9.	Support and encourage creativity, inventiveness and participation in product innovation and improvement	☐	☐	☐	☐	☐
10.	Invite and use feedback and ideas from external partners (customers, suppliers, research institutes) to improve our product development practices and performance	☐	☐	☐	☐	☐

11. Adapt to environmental changes and in the short time by innovating and improving our products	☐	☐	☐	☐	☐
12. Use mechanisms such as kaizen, improvement teams and incentives to systematically and continuously improve our performance	☐	☐	☐	☐	☐

Innovation performance

Over the past three years, our performance relative to our main competitors was, <u>on average</u>	**Much worse**		**Equal**		**Much better**	
Overall innovation performance						
13. The development of interchangeable parts across products that can be reconfigured into a wide variety of end products	☐	☐	☐	☐	☐	
14. Development of new products that differ substantially from our existing products	☐	☐	☐	☐	☐	
15. Development of environmentally friendly products (requiring less and/or less toxic material, are recyclable, and/or require less and/or recyclable packaging)	☐	☐	☐	☐	☐	
16. Project planning accuracy (e.g. percentage of projects over-running planned project lead time, time-to-market or budget)	☐	☐	☐	☐	☐	
17. Launch of “smart” (digitalized, intelligent) products (with in-built sensors, microprocessors, memory) (Internet of Things and Services)	☐	☐	☐	☐	☐	☐
18. The use of product platforms as a basis for future product variety and options						
19. Total new product development costs as a percentage of sales	☐	☐	☐	☐	☐	
20. Number of patents obtained						
21. Employee performance (e.g. health and safety, quality of life, motivation and satisfaction; education, knowledge and skills)	☐	☐	☐	☐	☐	